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A survey on personality-aware recommendation systems

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Abstract
With the emergence of personality computing as a new research field related to artificial intelligence and personality psychology, we have witnessed an unprecedented proliferation of personality-aware recommendation systems. Unlike conventional recommendation systems, these new systems solve traditional problems such as the cold start and data sparsity problems. This survey aims to study and systematically classify personality-aware recommendation systems. To the best of our knowledge, this survey is the first that focuses on personality-aware recommendation systems. We explore the different design choices of personality-aware recommendation systems, by comparing their personality modeling methods, as well as their recommendation techniques. Furthermore, we present the commonly used datasets and point out some of the challenges of personality-aware recommendation systems.

Keywords Recommendation systems · Personality computing · Personality-aware recommendation · Social computing · Collaborative filtering · Personality detection · Deep-learning · Hybrid filtering · Social recommendation

1 Introduction

Personality Computing is the interdisciplinary study field that focuses on the integration of personality psychology theories with computing systems. It has been proven that leveraging personality theories could help overcoming user modeling challenges. Personality computing has been applied in many domains and research directions, and the number of scientific publications within the scope of personality computing has dramatically increased within the last decade. The integration of user personality traits into the computing system has created new research directions, such as automatic personality recognition (APR), and helped to accelerate existing research directions as well, such as human-robot interaction (Cai et al. 2020) and social computing (Dhelim et al.

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2021b) research. Personality computing has also enabled recommendation systems to understand user preferences from a different perspective. A new type of recommendation system that leverages the user's personality trait to improve the recommendations had emerged. This group of systems is known as personality-aware recommendation systems. This new type of recommendation systems has proven effective in solving the challenges of conventional recommendation systems. Such as the cold-start problem, when the system does not have enough data about the preferences of the user, free-riders and data sparsity problems, to name a few.

In the recent few years, we have witnessed a rapid proliferation of personality-aware recommendation systems. While all of these recommendation systems incorporate the user's personality traits in the recommendation process, however, these systems use different recommendation techniques, and they are designed to recommend different content. Therefore, in this paper, we conduct a comprehensive survey of the literature of personality-aware recommendation systems. Few works surveyed some research direction in the field of personality computing. In 2014, Vinciarelli and Mohammadi (2014a) surveyed the publications that used the user's personality in computing systems, and they coined the term personality computing. In 2017, Kaushal and Patwardhan (2018) surveyed the literature on APR from online social networks. Similarly, in 2019, Mehta et al. (2020b) surveyed the literature on deep-learning-based personality APR. However, as far as we know, we are the first who survey the literature of personality-aware recommendation systems. In Table 1, we list some of the recent surveys in the field of personality computing, along with their focus scope and publication year.

The main focus of the current survey is personality-aware recommendation system. Specifically, we cover all the works that use the user's personality information for recombination services. We focus on works published between 2009 and 2021. We adapted PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework guidelines (Moher et al. 2010) to select publications related to personality-aware recommendation systems. As shown in Fig.1, initially, 669 related papers between January 2009 and April 2021 were identified after searching Google Scholar, Elsevier, IEEE Xplore digital library, ACM Digital Library, and Springer. for articles related to the following research queries: "personality computing", "personality-aware", "recommendation system", "personality recommendation", "personality-based", "social recommendation", "social computing", "personality collaborative filtering", "personality content filtering", "social computing", "social-aware", "personality modeling", "user personality". The searches were limited to articles written in English. 956 additional articles were identified as related works by following the citations map of the initially identified articles. After removing duplicated papers, a total of 1625 articles were gathered in the identification phase. In the screening phase, based on the title and abstract screening 1205 articles were excluded for not meeting the inclusion criteria. The majority of these articles either use personality information for other tasks, or they did not use personality information for recommendation. 285 articles were excluded in the eligibility phase after full-text reading. Finally, 135 articles were qualified for final inclusion.

The remainder of this paper is organized as follows: Section 2 shows the main differences between conventional recommendation systems and personality-aware recommendation systems. In Sect. 3, we systematically classify existing personality-aware recommendation system techniques. Section 4 reviews some of the works that proposed personality-aware recommendation systems in the last few years. Section 5 presents some of the commonly used datasets and benchmarks related to personality-aware recommendation systems. Section 6 discusses some of the challenges that face personality-aware

Table 1 Related surveys and reviews

Research field	Publication	Scope description	Year	Note
Personality computing	Vinciarelli and Mohammadi (2014a)	A general survey on personality computing	2014	Vinciarelli and Mohammadi coined the term "Personality computing"
	Wright (2014)	Commentary about Vinciarelli and Mohammadi (2014a)	2014	Wright explain his perspective about personality computing as a personality psychologist
	Vinciarelli and Mohammadi (2014b)	A complement of Vinciarelli and Mohammadi (2014a) by the same authors.	2014	Vinciarelli and Mohammadi replied on the commentary of Wright (2014), and discussed the future direction of personality computing
Automatic personality recognition	Jacques et al. (2019)	A survey on vision-based personality detection	2019	The authors have surveyed only image-based and video-based personality detection
	Kaushal et al. (2018)	A survey on user personality detection from online social networks	2018	
	Mehta et al. (2020b)	A survey on deep learning based personality detection.	2019	
	Bhavya et al. (2020)	A review on deep learning based personality detection from online social networks.	2019	These works surveyed textual, as well as non-textual (image, video, voice) personality detection
	Kedar et al. (2015)	A review on various approaches used for personality assessment	2015	
	Finnerty et al. (2016)	A review on the data sources and the features used for automatically infer personality	2016	
	Azucar et al. (2018)	Review on Big-Five personality traits from digital footprints on social media	2017	
	Dandanavara et al. (2018)	A review on text-based personality prediction from online social networks	2019	The authors have reviewed only text-based personality detection

Table 1 (continued)

Research field	Publication	Scope description	Year	Note
Personality in human-robot interaction	Santamaria et al. (2017)	A review on research methods for measuring personality in human-robot interaction	2017	
	Robert (2018)	A review on personality in human-robot interaction	2019	These works focus on robots' artificial personality traits and the application of personality computing in human-robot interaction
	Robert et al. (2020)	A review on personality in human-robot interaction	2020	
	Mou et al. (2020)	A review on the personality of robots	2020	

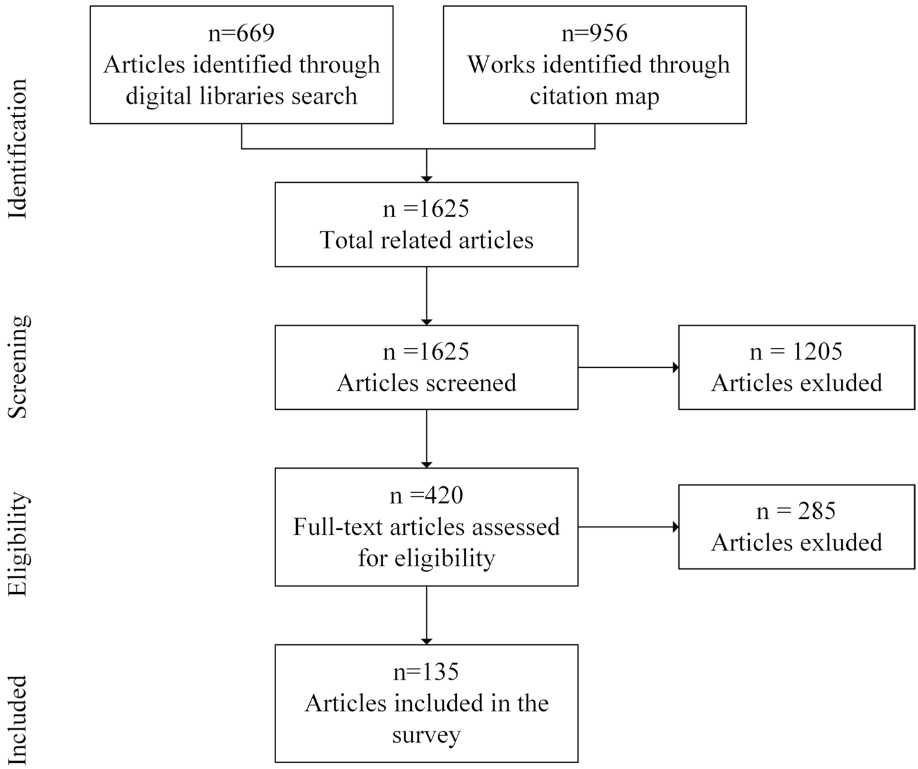

Fig. 1 PRISMA flowchart of the review phases

recommendation systems and also lists some of the open issues and research challenges. Finally, Sect. 7 concludes this survey and offers concluding remarks.

2 Personality models and recommendation systems

Historically, recommendation systems are divided into three main categories, collaborative filtering approaches, content filtering approaches and hybrid filtering approaches. Collaborative filtering is inspired by the fact that "people who agree on the past, probably will agree in the future". In practice, in order to recommend new items to a given user u_x, collaborative filtering systems determine a group of users that have a similar rating with user u_x, these users are called the neighbors of user u_x. After finding the group of neighbors, the system finds the set of items that share a high rating among these neighbors, and subsequently recommend these items to user u_x. While content filtering approaches, compute the similarity between previous matched items and the suggested items, regardless of the neighbors' ratings. Finally, hybrid approaches use a combination of these two techniques. Similar to the conventional recommendation systems, personality-aware recommendation systems also use similar recommendation techniques, the only difference is that they add the user's personality information in the recommendation process. In Figs. 2 and 3, we show the main differences between conventional and personality-aware recommendation

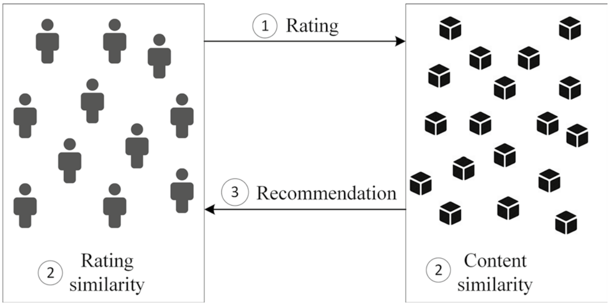

Fig. 2 Conventional recommendation systems

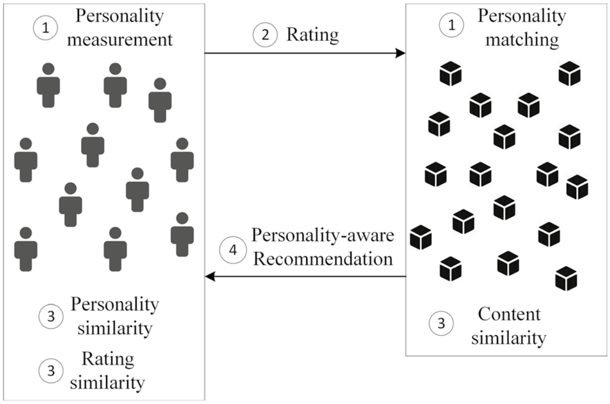

Fig. 3 Personality-aware recommendation systems

systems. Conventional recommendation systems mainly have three stages. Firstly, the rating phase, where the users express their interests by rating some items. The second stage is the filtering phase, either collaborative filtering, content filter or hybrid filtering as mentioned above. Finally, at the recommendation phase, the system recommends the items yielded by the filtering phase.

As shown in Fig. 3, personality-aware recommendation systems add two more phases before the rating phase and change the filtering stage as well. Personality measurement phase, the system assesses the personality type of users using a personality assessment questionnaire that the users need to answer during registration, or by applying an APR scheme on the user's previously available data, such as online social network data. While in personality matching phase, the system tries to match user personality type with relevant items by computing the matching likelihood between the user and these items. The matching is computed based only on the personality information of users and some personality features of the item, such as a product brand in product recommendation or personality type of actors in the case of movie recommendation. Personality matching is performed either using lexical matching by linking textual description of the items with the associated personality types, or using a fine-grained rules that can match items with personality types. It is worth noting that at personality matching phase, the system does not have any information about the user's ratings, which help to alleviate the effects of cold-start problem, one of the most challenging problems in the literature of recommendation systems. Personality-aware recommendation systems also change the filtering phase, by incorporating the personality information in similarity measurement to determine the neighbors of each user. The primary objective of filtering phase in the conventional collaborative filtering is to determine the set of neighbors that have similar ratings with the current user, a process known as neighborhood formation. In personality-aware recommendation system, the similarity between the users is computing based on their personality trait similarity or using a hybrid personality-rating similarity measurement, and the resulting set of neighbors are similar in terms of personality traits to the studied user.

2.1 Personality models

Various personality theories tried to define human personality and represent it in measurable scale. One of the most widely used personality theories is known as the Five Factors Model (FFM) (Goldberg 1990), also known as Big-Five personality traits theory. FFM theory suggests that the human personality is defined by measurable five factors/traits: Openness to experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism, sometimes abbreviated as OCEAN or CANOE. FFM is by far the most used theory in the personality-aware recommendation domain. However, very few works still use other less known personality model, such as the HEXACO model (Ashton et al. 2014), which extends the FFM to include a sixth trait known as Honesty-Humility (H), and replace Neuroticism by Emotionality. Therefore HEXACO traits are: Honesty-Humility (H), Emotionality (E), Extraversion (X), Agreeableness (A), Conscientiousness (C), and Openness to Experience (O). Another personality model rarely used in personality computing is the Myers–Briggs Type Indicator (MBTI) (Boyle 1995), unlike FFM and HEXACO, 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 different score in multiple traits. MBTI defines four categories: introversion or extraversion, sensing or intuition, thinking or feeling, judging or perceiving. One letter from each category is taken to produce a four-letter personality types, e.g. "INFJ" or "ENFP", which makes 16 possible personality types.

2.2 Personality measurement

The personality measurement is the most important phase of personality-aware recommendation system, as any misidentification of the user personality type could negatively influence the accuracy of the recommendation system. In personality computing, there are two main methods for personality measurement, personality assessment questionnaires and APR. Generally, questionnaires based personality measurement is more accurate than APR. However, in the context of personality computing, APR are relatively easier to conduct, as they can be applied to the user's existing data, without the need to burden the user with long questionnaires. In this subsection, we discuss the different personality assessment questionnaires and APR techniques and classify some of the existing personality-aware recommendation systems based on the their personality assessment method.

2.2.1 Personality assessment questionnaires

In the study field of personality psychology, self-report personality questionnaires have been widely used to reveal personality differences among individuals. Questionnaires in which people estimate their character and behaviors are the most commonly used mean for personality assessment. The answers are typically in the format of five-level Likert scale

Table 2 The BFI-10 personaltiy questionnaire for FFM

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 tend to find fault with others	Agreeableness
9	I do a thorough job	Conscientiousness
10	I am relaxed, handle stress well	Neuroticism

(strongly agree, agree, neither agree or disagree, disagree and strongly disagree). For FFM, there are many personality questionnaires of various lengths (number of items). The widely used long questionnaires include NEO Five-Factor Inventory (NEO-FFI, 60 items) (Aluja et al. 2005), NEO-Personality-Inventory Revised (NEO-PI-R, 240 items) (Costa Jr and McCrae 2008), International Personality Item Pool (IPIP-NEO, 300 items) and the Big-Five Inventory (BFI, 44 items) (Rammstedt and John 2007). In the context of personality-aware recommendation system, these questionnaires could be directly solicited from the users during registration. Filling a long questionnaire is a time-consuming task, the user might get bored and may not fill the questionnaire carefully, which could lead to an irrelevant recommendation in the future. Therefore, short questionnaires (Rammstedt and John 2007; Gosling et al. 2003; Topolewska et al. 2014) (5-10 items) are preferred in personality-aware recommendation systems, as these questionnaires are much easier to fill. For FFM, the most prominent short questionnaires are BFI-10 (a short version of BFI with 10 items) and Ten-Item Personality Inventory (TIPI, 10 items) (Gosling et al. 2003). Table 2 shows the items of BFI-10.

There are two main drawbacks of self-assessment questionnaires. The first limitation is the self-bias problem (Pedregon et al. 2012), when the subjects tend to give the wrong answer to some of the undesired social characteristics in certain circumstances. For example, when answering a recruitment personality questionnaire, most of the subjects give inaccurate answers to questions like “I get nervous easily”, “I tend to be lazy”, because these are undesired characters in employees. The self-bias does not affect personality-aware recommendation systems, because users have no benefit in misleading the system. The second drawback is known as the reference-group effect (Youyou et al. 2017a), in which the answers given by the subject is relative to his surrounding environment (Dhelim et al. 2016). For example, an introvert engineer might think he is extrovert if he is surrounded by a group of even more introvert engineer friends (Ning et al. 2018). In Table 3, we list FFM personality assessment questionnaires used in the literature of personality-aware recommendation system.

2.2.2 Automatic personality recognition

The assessment of user’s personality using a questionnaire is not possible in certain circumstances, for example when analyzing an existing anonymous dataset, or when filling a personality questionnaire is not convenient. APR could be used to solve this dilemma. APR

Table 3 FFM questionnaires for personality-aware recommendation systems

Questionnaire	Item count	Recommendation system
TIPI	10	Berkovsky et al. (2017); Braunhofer et al. (2014a, b); Buettner (2017); Chan et al. (2018); Dhelim et al. (2020a, 2020b); Elahi et al. (2013); Ferwerda et al. (2017a); Hu and Pu (2010b, 2010a, 2011); Karumur et al. (2016, 2018); Liu and Hu (2020); Melchiorre and Schedl (2020); Moscato et al. (2020); Nguyen et al. (2018); Sun et al. (2018); Wang (2015); Wu et al. (2019); Zheng and Subramaniyan (2019); Zhou et al. (2011)
BFI-44	44	Alves et al. (2020); Balakrishnan and Arabi (2018); Bolock et al. (2020); Cheng and Tang (2016); Ferwerda et al. (2016); Kim and Kim (2019); Odić et al. (2013); Potash and Rumshisky (2016); Quijano-Sanchez et al. (2010); Schedl et al. (2016); Sofia et al. (2016); Ting and Varathan (2018); Wu et al. (2013, 2018))
BFI-10	10	Guntuku et al. (2015a, 2015b); Li et al. (2019, 2020); de Lima et al. (2018); Roffo and Vinciarelli (2016); Roffo (2016); Scott et al. (2016a, 2016b)
NEO-FFI	60	Shayegan and Valizadeh (2020); Yusefi Hafshejani et al. (2018)
NEO-PI-R-60	60	Khodabandehlou et al. (2020)
IPIP-336	336	Fernández-Tobías et al. (2016); Fernández-Tobías and Cantador (2014)
IPIP-100	100	Sun et al. (2020); Youyou et al. (2017b)
IPIP-NEO-60	60	Ning et al. (2019)
IPIP-50	50	Karumur and Konstan (2016); Nalmpantis and Tjortjis (2017); Neehal and Mottalib (2019); Tkalcic et al. (2010)
IPIP-44	44	Mukta et al. (2016)
IPIP-25	25	Wu and Chen (2015)
IPIP-20	20	Cantador et al. (2013); Fernández-Tobías and Cantador (2015)
FIPI	5	Braunhofer et al. (2015)

is the process of automatic mapping the data related to a subject to a personality score that represents the personality profile of that subject. In the context of user personality from online social network data, APR schemes are generally divided into three classes. Text-based APR, where the source data is in text format such as social media posts. Multimedia-based APR, where the source data is an image, voice or video, such as social media profile photos. And finally, behavior-based APR, where the source data represent a set of behavioral patterns of the user, such as gaming behaviors or browsing behaviors. Text-based APR generally has higher accuracy than multimedia-based APR and behavior-based APR.

Text-based APR is inspired by the fact that some language psychology theories claim that the choice of words can reveal some psychological states such as emotions and personality traits of the subject (Hirsh and Peterson 2009; Polignano et al. 2021). Therefore, text-based APR analyzes the word choice frequency to infer the user's personality traits from his social media posts or messages. One of the most common prominent techniques for text-based APR is Linguistic Inquiry and Word Count (LIWC) (Tausczik and Pennebaker 2010). LIWC categorizes the analyzed text into various psychologically relevant sets known as "buckets" like 'function words' (e.g., conjunctions, articles, pronouns), 'social processes' (e.g., mate, talk, friend) and 'affective processes' (e.g., happy, nervous, cried). Following that, LIWC measures the frequency of words in each of these buckets and predicts the personality traits of the subject accordingly. Another famous linguistic database is the Medical Research Council (MRC) psycholinguistics database. Linguistic analysis model like LIWC and MRC have been proven to achieve acceptable accuracy to detect the user's personality traits from its text. For instance, Han et al. (2020) introduced an APR model based on personality lexicon by analyzing the correlations between personality traits and semantic categories of words, and extract the semantic features of user's microblogs to construct a prediction model using word classification algorithm. On the other hand, multimedia-based APR detects the user's personality traits by analyzing it is related to photos or video and try to associate the features of these data with the facets of personality traits. For instance, users who frequently post photos related to art might achieve a high score openness trait. Li et al. (2020) introduced a framework that predicts the aesthetics distribution of an image and the Big-Five personality traits of people who liked the image. Finally, behavior-based APR detects the user's personality trait by analyzing behavioral patterns and associate them with relevant dominant traits. Annalyn et al. (2018) studied the relationship content labels "tags" generated by users from Goodreads.com, and match it with personality scores collected from Facebook users. Vinciarelli and Mohammadi (2014a) surveyed the literature of APR and classify the reviewed works, and Kaushal et al. (2018) surveyed APR methods that leverage online social networks as a data source. While Jacques et al. (2019) surveyed vision-based APR methods, and recently, Mehta et al. (2020b) and Bhavya et al. (2020) surveyed deep-learning-based APR.

In Table 4, we summarize some of the key recent APR works that were not covered in these surveys. it is worth mentioning that some platforms offer Application Programming Interface (API) for APR by analyzing the user's social media data. For instance, IBM Watson Personality Insights[1] uses linguistic analytics to infer individuals' intrinsic personality characteristics, including Big Five, from digital footprints such as email, text messages, tweets, and forum posts. Another prominent APR API is Cambridge's ApplyMagicSauce API[2], which translates individuals' digital footprints into psychological profiles.

[1] www.cloud.ibm.com/apidocs/personality-insights.

[2] www.applymagicsauce.com.

Table 4 APR literature review

APR type	Publication	Description	Applied on
Text-based APR	Silva et al. (2018)	Proposed a supervised models for APR of text in Brazilian Portuguese	Facebook posts
	Han et al. (2020)	Used word embedding techniques and prior-knowledge lexicons to automatically construct a Chinese semantic lexicon suitable for personality analysis	Weibo posts
	Sun et al. (2020)	Proposed a model of group-level personality detection by learning the influence from text generated networks	Wikipedia articles
	Darliansyah et al. (2019)	Take advantage of Neural Network Language Model for personality detection from short texts by using a unified model that combines a Recurrent Neural Network named Long Short-Term Memory with a Convolutional Neural Network.	Tweets
	Santos et al. (2020)	Discussed the effectiveness of using psycholinguistic knowledge in APR, and performed series of individual experiments of APR	Facebook posts
	Mehta et al. (2020a)	Propose a novel deep learning-based model which integrates traditional psycholinguistic features with language model embeddings to predict personality	Essays

Table 4 (continued)

APR type	Publication	Description	Applied on
Multimedia-based APR	Li et al. (2020)	Introduced a framework that predicts the aesthetics distribution of an image and Big-Five personality traits of people who like the image	Flickr images
	Kim et al. (2018)	Used computer vision techniques to detect users personality from their shared pictures. An online survey of 179 university students was conducted to measure user characteristics, and 25,394 photos in total were downloaded and analyzed from the respondents' Instagram accounts	Instagram images
	Segalin et al. (2017)	Used computational aesthetics to infer the personality traits of Flickr users from their galleries, their method maps low-level features extracted from the pictures into numerical scores corresponding to the Big-Five traits, both self-assessed and attributed	Flickr images
	Ferwerda et al. (2015a)	Conducted an online survey, by analyzing 113 participants and 22,398 extracted Instagram pictures, they conclude that there is correlation between distinct picture features and personality traits	Instagram images
	Zhu et al. (2020)	Introduced an end-to-end weakly-supervised dual convolutional network for personality detection, composed of a classification network and a regression network. The classification network detects personality class-specific attentive image regions. While the regression network is used for detecting personality traits	Flickr images
	Guntuku et al. (2018)	Propose a personality traits detection model, and analyzed collection of images and users who tag as favorite	Flickr images
	Zhang et al. (2020)	Proposed PersEmoN, an end-to-end trainable and deep Siamese-like network. PersEmoN is composed of two convolutional network branches, the first for emotion and the second for personality traits. Both networks share their bottom feature extraction module and are optimized within a multi-task learning framework	YouTube videos

Table 4 (continued)

APR type	Publication	Description	Applied on
Behavior-based APR	Tadesse et al. (2018)	Analyzed and compared four machine learning models to investigate the relationship between user behavior and Big-Five personality traits	Facebook profiles
	Annalyn et al. (2018)	Investigated the relationship between user book preferences by analyzing labels "tags" generated by users, and match it with personality scores collected from Facebook users	Goodreads profiles
	Fong et al. (2015)	Discussed personality inferences and intentions to befriend based solely on online avatars	Digital avatars
	Nave et al. (2018)	Investigated the possibility of personality prediction using musical preferences. Their finding using data of active listening and Facebook likes show that reactions to unfamiliar musical excerpts predicted individual differences in personality	Facebook profiles

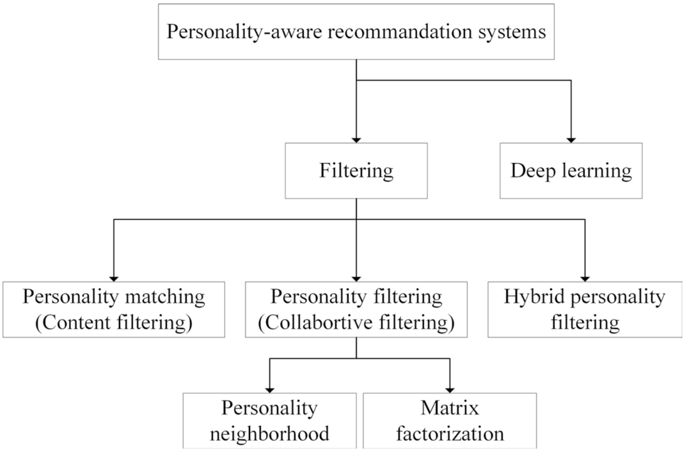

Fig. 4 Personality-aware recommendation systems classification

3 Personality-aware schemes classifications

After the emergence of personality computing, in the last decade, we have witnessed an unprecedented proliferation of personality-aware recommendation systems. These systems use different recommendation techniques, and in some cases, the recommendation process depends on the nature of the recommended content. In this section, we classify the recent personality-aware recommendation system based on the recommendation technique. Personality-aware recommendation systems are roughly divided into four main classes, filtering-based methods and deep-learning-based methods. Fig. 4 shows the classification that we will be using to classify the recent proposed personality-aware recommendation systems. Filtering methods are divided into three classes, personality filtering, personality matching and hybrid filtering.

3.1 Personality filtering

Personality-aware recommendation systems that leverage the conventional collaborative filtering technique to filter users with similar personalities are known as personality filtering methods. Personality filtering methods in turn could be further divided into personality-neighborhood methods and matrix factorization methods.

3.1.1 Personality neighborhood methods

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. While there are many proximity functions, the 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 rating similarity function $SimR(u_x, u_y)$ as shown in Eq. (1), where R_x and R_y is the sets of the previous rating 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.

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

Many personality-aware recommendation systems extend this approach to measure the personality similarity between users is computed using the personality similarity function $SimP(u_x, u_y)$ as shown in Eq (2), where $\overline{p_x}$ and $\overline{p_y}$ is the average value of the personality traits vector for user u_x and u_y respectively, and p_x^i is the i^{th} trait in the personality traits vector

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

However, some other works opted to use other proximity functions to measure the personality similarity between users. In Table 5, we summarize some commonly used personality similarity proximity functions.

After computing the similarity among users and eventually establishing the neighborhood of each user, the prediction score is computed by aggregating the rating of neighborhood users and the similarity with these users (Khelloufi et al. 2021). Formally, let $Score(u, i)$ denote the predication score that user u will give to item i, the prediction score is computed using Eq. (3)

$$Score(u, i) = \overline{r_u} + k \sum_{v \in \Omega_u} Sim(u, v)\,(r_{v,i} - \overline{r_v}) \tag{3}$$

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. Different works used a different design of the proximity function that measures the total similarity $Sim(u, v)$. In this regard, there are three main designs. Some works ((Wu and Chen 2015)) simply use the personality similarity function $SimP(u, v)$ instead of $Sim(u, v)$. While other works ((Ning et al. 2019)) opted to use a combination of the personality similarity function $SimP(u, v)$ and the rating similarity function $SimR(u, v)$. Finally, some other works ((Dhelim et al. 2020b, a, 2021a)) use other social factor similarity functions such as user interests similarity along with the rating similarity and personality similarity.

3.1.2 Matrix factorization methods

In personality-enhanced matrix factorization methods, the conventional matrix factorization algorithm is extended to incorporate the user's personality traits along with its ratings. In the conventional matrix factorization method, the user-item interaction matrix is decomposed to the product of two low-dimensionality rectangular matrices that represent the represent users and items in a lower dimensional latent space, this is done by applying dimensionality reduction algorithm such as singular value decomposition. Formally, let $p_u \in \mathbb{R}^k$ and $q_i \in \mathbb{R}^k$ denote the latent feature vector of user u and item i respectively. In the conventional matrix

Table 5 Personality-based similarity measurement

Proximity function	Function	Publication	Note
Pearson correlation coefficient	$SimP(u,\ v) = \frac{\sum_i (p_u^i - \overline{p_u})(p_v^i - \overline{p_v})}{\sqrt{\sum_i (p_u^i - \overline{p_u})^2 \sum_i (p_v^i - \overline{p_v})^2}}$	Asabere et al. (2018, 2020); Hu and Pu (2010b, 2011); Ning et al. (2019); Recio-Garcia et al. (2009); Sun et al. (2018); Xia et al. (2017); Yusefi Hafshejani et al. (2018)	Used by most of the state-of-the-art personality-aware recommendation systems
Normalized Euclidean distance	$SimP(u,\ v) = \frac{1}{1+\left(\sqrt{\sum_k w_k^2 (P_u^k - P_v^k)^2}\right)}$	Tkalcic et al. (2010); Wu et al. (2018)	w_k is the weight of the kth personality trait
Euclidean distance	$Eucl = \sqrt{(E^{BFI-S} - E^{PPS})^2 + (A^{BFI-S} - A^{PPS})^2 + (C^{BFI-S} - C^{PPS})^2}$	Buettner (2017)	E^{BFI-S} is the extraversion trait value for the user, and E^{PPS} is the extraversion trait value assigned to a product. Similarly A is the agreeableness trait, and C is conscientiousness
Cosine similarity measure	$SimP(u,\ v) = \frac{\sum_k P_{u,k}.P_{v,k}}{\sqrt{\sum_k {P_{u,k}}^2}\sqrt{\sum_k {P_{v,k}}^2}}$	Onori et al. (2016); Wu and Chen (2015); Yang and Huang (2019); Zheng and Subramaniyan (2019)	Cosine similarity is a dot product of unit vectors, unlike Pearson correlation, which is cosine similarity between centered vectors
Spearman's correlation coefficient	$SimP(u,\ v) = \frac{\sum_k (s_{u,k} - \overline{s_u})(s_{v,k} - \overline{s_v})}{\sqrt{\sum_k (s_{u,k} - \overline{s_u})^2 \sum_k (s_{v,k} - \overline{s_v})^2}}$	Fernández-Tobías and Cantador (2014)	Where $s_{u,k}$ is the position of $P_{u,k}$ in the decreasing order ranking of Big-Five scores
Hellinger-Bhattacharya Distance	$SimP(u,\ v) = \frac{1}{\sqrt{2}} * \sqrt{\sum_{i=1}^{5} \left(\sqrt{u_i} - \sqrt{v_i}\right)^2}$	Chakrabarty et al. (2020)	

factorization method, the user u's preference to item i is estimated by computing the dot product of user u and item i latent feature vectors, as shown in Eq. (4).

$$\hat{r}_{ui} = p_u \cdot q_i \tag{4}$$

Personality-enhanced matrix factorization extends this by incorporating the user's personality traits, and other occasionally other social attributes. They introduce an additional latent feature vector $y_a \in \mathbb{R}^k$ for each social attribute $a \in A$. Eq. (4) is extended to incorporate these attributes as shown in Eq. (5). It is worth noting that some works consider the Big-Five personality score vector as the only attribute, as in (Fernández-Tobías et al. 2016). While some other works add other social attributes in addition to the personality, for instance, in (Elahi et al. 2013) the user's gender, age group and the scores for the Big-Five personality traits are used as attributes.

$$\hat{r}_{ui} = q_i \cdot \left(p_u + \sum_{a \in A} y_a \right) \tag{5}$$

3.2 Personality matching methods

This approach is similar to the conventional content filtering approach. In the personality matching method, a personality score is assigned to each item. This is done either using content analysis, attribute analysis or a hybrid approach. In the content analysis, the system assigns a personality score to an item by applying an APR on the content of that item, such as the textual description, labels and category. For example, in Buettner (2017) a product personality assessment method known as product personality scale (Mugge et al. 2009) was used to assess the personality of the items. While in attribute analysis, the system assigns a personality score to an item by analyzing the attribute of that item, such as the personality traits of users that interacted with that item. For instance, in Yang and Huang (2019) the personality P_{G_i} of a video game G_i is assigned by computing the average personality traits of users who played G_i as $P_{G_i} = \frac{\sum_{U_j \in o_{G_i}} P_{U_j}}{\left| o_{G_i} \right|}$. Personality matching is usually applied if we can observe a common matching criteria between the recommended content and the target user, which eliminate the need for extensive computing in order to find the neighborhood set from one hand, and mitigate the cold start on the other hand. Xiao et al. (2018) used personality matching approach for followee recommendation, the total personality matching (TPM) score between a given user u and the potential blogger pf is computed as shown in Eq. (6):

$$TPM(u, pf) = \mu(MS(u, pf, dim)) \tag{6}$$

where $MS(u, pf, dim)$ denotes the personality matching score of the user u and the potential recommendation followee pf in a the respective dimension, and μ is the average value of each dimension.

3.3 Hybrid personality filtering methods

Hybrid personality filtering methods combine the technique of personality filtering on the user's space, and personality matching on the items space. Hybrid personality filtering has been proven as an effective method that leverages the advantages of personality filtering and personality matching methods. Ning et al. (2019) used a hybrid personality filtering approach for friend recommendation, where personality filtering is used to find users with similar ratings and personality matching is used to filter the item space (since it is a friend recommendation system, the items represent potential friends). Similarly, Yang et al. (2019) also used hybrid personality filtering for a game recommendation, where personality filtering is used to determine user with similar game ratings, and personality matching is used to attribute personality to games.

3.4 Deep learning methods

In recent years, deep learning has revolutionized the domain of recommendation systems by leveraging deep learning models, such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and Autoencoder, to name a few. Personality-aware recommendation systems are not an exception to this revolution. Deep learning is either used to detect the user personality of the users or in the recommendation process itself. The choice of deep learning model used for personality detection and personality-aware recommendation depends on the type of source data of users. Deep learning model that are inspired by natural language processing, such as the n-gram model, are suitable for personality detection and content recommendation from textual source data. For instance, Majumder et al. (2017) proposed deep CNN for document-level APR, the CNN extracts monogram, bigram and trigram features from the document text and each word was represented in the input as a fixed-length feature vector using Word2Vec (Mikolov et al. 2013) model, finally linguistic features (e.g. LIWC, MRC) are concentrated and fed to fully connected layer for personality traits prediction. Similarly, deep learning models that are designed for image and video processing are suitable for personality detection and personality-aware recommendation using non-textual personality data. Wei et al. (2017) proposed Deep Bimodal Regression (DBR) framework for apparent personality analysis from videos and images. DBR modified the common CNNs for incorporating essential visual cues. Besides the source data format, the recommended content nature could also influence the choice of deep learning models to be used as personality-aware recommendations. For example, Chi-Seo et al. (2020) introduced a system that employs deep learning to classify and recommend tourism types that are compatible with the user's personality. The model is composed out of three layers, each layer incorporates a service provisioning layer, the recommendation service layer, responsible to produce recommended services based on user information inputted, and the adaptive definition layer, that learns the types of tourism that fits for the user's personality types.

4 Literature review of personality-aware recommendation systems

In the last few years, we have witnessed a rapid proliferation of personality-aware recommendation systems. In this section, we review the literature on personality-aware recommendation systems in different application domains.

4.1 Friend recommendations

In the literature of social networks, many personality-aware friend recommendation systems have been proposed, 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. Similarly, Chakrabarty et al. (2020) designed a personality-aware friend recommendation system name FAFinder (Friend Affinity Finder). FAFinder uses Hellinger-Bhattacharyya Distance (H-B Distance) to measure the user's Big-Five similarity and recommend friends accordingly. While Bian et al. (2012) designed and implemented Matchmaker, a personality-aware friend recommendation system that recommends friends to users on Facebook by matching and comparing user's online profile with the profiles of TV characters. For example, if Facebook user X is similar to TV character 1, and Facebook user Y is similar to TV character 2, and character 1 and character 2 are friends in the same TV show, then the Matchmaker system recommends user X to become friends with user Y. Whereas, Neehal et al. (2019) introduced a personality-aware friend recommendation framework, which uses a 3-Layered artificial neural network (ANN) for friend preference classification and a distance-based sorted subset selection function for friend recommendation, the proposed friend recommendation system achieved a relatively high precision=85%, recall=85% and f1-measure=82% in the friend choice classification task. Tommasel et al. (2016; 2015) studied the effects of user personality on the accuracy of followees prediction on microblogging social media. The authors analyzed how the user's personality character influence the followees selection process by incorporating personality traits with state of the art followee predicting factors. To prove the effectiveness of proposed followee prediction algorithm, the author collected a Twitter dataset by crawling the account of 1852 users, and only users that English is their tweeting language were selected. They tested the content-based followee prediction algorithm with and without including the user's personality traits. Their results showed that incorporating personality traits can enhance the followee recommendations. While Tommasel et al. (2015) analyzed 3 different similarity factors. Firstly, they calculated the total similarity by taking into account the Big-Five personality factors as a whole. Secondly, they calculated the dimension to dimension similarity measure by taking into account every individual personality traits separated from each other. Finally, they calculated a cross dimension similarity measurement by taking into account every personality faced in relation to the others. Their results showed that personality traits must be regarded as a distinctive factor in the process of followee prediction. However, personality dimensions should not be analyzed as a whole because the overall personality similarity measurement might not precisely assess the actual matching between users. The data analysis proves the existence of relations among the individual personality facades. Therefore, the importance of assessing each personality trait with respect to other users. Similarly, Xiao et al. (2018) introduced a personality-aware followee recommendation system based on sentiment analysis and text semantics named PSER , they proposed model combines the user attributes with the Big-Five traits to recommend new followees. PESR quantitatively analyses the effects of considering user personality in followee selection by incorporating personality traits with text semantics of micro-blogging and sentiment analysis of users. Dhelim et al. (2018; 2018) proposed a smart home architecture that use the user's personality information to optimize the social relationships among the smart home residents. In the same vein, Mukta et al. (2016) proposed a technique to detect homophily by analyzing the Big-Five personality traits of users in an egocentric network such as Facebook. Their results indicate that homophilies correctly cluster ranged from 73% to 87% users for different personality traits. Wu et al. (2017b) investigated the correlation of similarity of personality and the strength of friendship and romantic relationship, and their results indeed provide evidence for personality similarity between friends and between romantic partners. Shayegan et al. (2020) introduced a personality-aware recommender system that leverage the Cosine similarity algorithm to explore and recommend relevant Telegram channels to users according to their personalities. Their results show a 65.42% satisfaction rate for the personality-aware recommender system based on the proposed personality analysis. Table 6 summarizes the literature of personality-aware friend recommendation systems.

4.2 Movies recommendations

Asabere et al. (2020) proposed ROPPSA, a personality-aware TV program recommendation system that leverages normalization and folksonomy procedures to generate group recommendations for viewers with similar personality traits and tie strength with a Target TV Viewer (TTV). Their results on the experimentation procedure show the advantages of ROPPSA compared to similar but personality-agnostic TV program recommendation system baselines, in terms of precision, recall and F-measure (F1), and arithmetic mean (AM). Balakrishnan et al. (2018) proposed a hybrid recommender system for movies named HyPeRM,, the proposed system includes the user's personality character in addition to their demographic information (e.g. sex and age) to enhance the precision of the recommendations. Big-Five personality trait was employed to measure the user's personalities. HyPeRM was tested based on the Root Mean Square Error of Approximation (RMSEA) and the Standardized Root Mean Square Residual (SRMR). Both theses metrics showed that HyPeRM outperformed the baseline variant (i.e. the recommendation without including the user's personality) in terms of the precision of the recommendation. Their work shows that movies recommendations can be improved by incorporating the viewers' personality traits. Similarly, Shanchez et al. (2011) proposed HappyMovie, a Facebook application for movie recommendations, HappyMovie uses three features for a movie recommendation, user personality, social trust with other users and the past movie ratings. Unlike other works, HappyMovie uses Thomas-Kilmann Conflict Instrument (TKI) personality model instead of Big-Five model. While Bolock et al. (2020) proposed a movie recommendation system based on the user's character. The system is adaptive in the way it uses a different recommendation algorithm for different users based on the used character criteria. The authors implemented a movie recommendation application to find the relationship between the user's character and the recommendation algorithm, they have used three main character dimensions, user personality, background and gender. On the relationship between personality and movie preferences, Golbeck et al. (2013) proved the positive correlation between personality and user's movie preferences. Using surveys and analysis of system data for 73 Netflix users, they proved correlation between personality and preferences for specific movie genres. Wu and Chen (2015) studied user personality inferences using implicit behaviors with movies, and the possibility to recommend movies base on the user's personality traits without user's explicit ratings. Specifically, they determined a set of behavioral features using experimental confirmation and proposed an inference method using Gaussian Process to fuse these features and subsequently detect the user's Big-Five personality traits. After that, they used the obtained personality information to enhance the collaborative filtering movie recommendation process. Scott et al. (2016a) investigated the relationship between personality and cultural traits with a perception of multimedia quality. They have compared three statistical models: (1) a baseline model to only include system factors; (2) an extended model to consider personality and culture; and (3) an optimistic model in which each participant is modeled. Based on these statistical findings, they

Table 6 Personality-aware friend recommendation systems

System	Factors	Technique	Model	Measure	Dataset
FAFinder (Chakrabarty et al. 2020)	Big-Five traits	Personality neighborhood	FFM	APR	Self-collected
Shayegan and Valizadeh (2020)	Big-Five traits	Deep-learning	FFM	NEO-FFI-60	Telegram
PersoNet (Ning et al. 2019)	Big-Five traits Harmony rating	Hybrid personality filtering	FFM	NEO PI-R-60	Self-collected
Neehal and Mottalib (2019)	Big-Five traits	Deep-learning	FFM	IPIP-50	myPersonality
PSER Xiao et al. (2018)	Big-Five traits User attributes	Personality matching	FFM	APR (LIWC)	Weibo
Youyou et al. (2017b)	Big-Five traits	Personality neighborhood	FFM	IPIP	myPersonality
Tommasel et al. (2016)	User behavior Big-Five traits	Personality neighborhood	FFM	APR (LIWC)	Twitter
Mukta et al. (2016)	Big-Five traits	Deep-learning	FFM	IPIP 44-version	Facebook
Tommasel et al. (2015)	User behavior Big-Five traits	Personality neighborhood	FFM	APR (LIWC)	Twitter
Tommasel et al. (2015)	Big-Five traits	Personality neighborhood	FFM	APR (LIWC)	Twitter
Matchmaker (Li et al. 2012)	Big-Five traits TV characters similarity	Personality matching	FFM	APR	Facebook
Bian and Holtzman (2011)	Big-Five traits TV characters similarity	Personality matching	FFM	APR	Facebook

trained and generalized the predictive models to include content, affect, system, and human factors. Hu et al. (2011) addressed the cold-start problem by incorporating human personality into the collaborative filtering framework, they have proposed three recommendation approaches: (1) a recommendation method based on user's personality information solely; (2) based on a linear combination of both personality and rating information; (3) used a cascade mechanism to leverage both resources. To test the effectiveness of the studied systems, they compared the proposed approaches with the conventional rating-based CF in two cold-start scenarios: sparse data sets and new users. Berkovsky et al. (2017) studied the effects of different recommendation and content filtering strategies on user trust. They evaluated the score of nine main factors of trust grouped and divided them into three dimensions and tested the different observations regarding the user's personality traits. Wu et al. (2018) introduced a generalized, dynamic personality-aware greedy re-ranking method to compute the recommendation list. Personality traits are utilized to estimate each user's diversity preferences, and also to minimize the effects of cold-start problem on collaborative filtering recommendations. Sofia et al. (2016) studied The Elaboration Likelihood Model (ELM) which clam that users with low motivation or ability to process the information given in the recommended item could eventually get persuaded to choose these item if appropriate peripheral cues enrich these recommendation. Moreover they applied Fuzzy-Set Qualitative Comparative Analysis (fsQCA) for personality-aware movie recommendation data analysis. Yi et al. (2016) introduced MBTI-CF, a personality-aware Webtoon recommendation system that leverages MBTI personality model to computer personality-based neighborhood. Their results suggest that the performance of MBTI-CF is more stable than that of the traditional CF when dealing with cold-start users. But the performance of the MBTI-CF is less accurate than that of the tradtional CF in normal settings. Khan et al. (2020) studied the relationship between human psychological attributes and their movie preferences. Specifically, they used the user's twitter data to extract her personality traits and values and predict her movie preferences. Following that, they extended their model to predict user rating behavior based on her tweets and the movie' storyline on IMDb. Table 7 summarizes the literature of personality-aware movie recommendation systems.

4.3 Music recommendations

The importance of including the user's personality traits in music recommendation systems have been discussed in many previous works. Ferwerda et al. (2017a; 2016) studied the correlation between personality and music genre preferences over different age groups, they combined the accounts of myPersonality dataset users with their Last.fm listening history. Their finding suggest that the openness trait shows most variation in listening to different music genres among the different age groups. Moscato et al. (2020) proposed a personality-aware music recommendation system based on the user's personality traits, moods and emotions, detected by analyzing the psychological observations of the user's behaviors within a social environment. Specifically, the user's personality traits and mood are embedded within a content-based filtering approach to obtain more accurate and dynamic recommendations. Liu et al. (2020) studied the effects of multiple information for music recommendation system, including personality traits and physiological signals obtained though wearable wristband. A dataset of 23 users and 628 song were collected from a user experiment, with physiological signals, matched personality, as well as music acoustic features. Specifically, they applied four regression machine learning algorithms to

Table 7 Personality-aware movie recommendation systems

System	Factors	Technique	Model	Test	Dataset
ROPPSA (Asabere et al. 2020)	Big-Five traits Target TV viewer	Personality neighborhood	FFM	APR	Self-collected
Bolock et al. (2020)	Big-Five traits User demography User rating	Personality neighborhood	FFM	NEO-PI-R	MovieLens
Khan et al. (2020)	Basic human values Big-Five traits	Personality matching	FFM	APR(IBM)	Twitter IMDb
Wu et al. (2018)	Big-Five traits	Personality neighborhood	FFM	BFI-44	Douban
HyPeRM (Balakrishnan and Arabi 2018)	Big-Five traits User demography	Personality neighborhood	FFM	BFI-44	Self-collected
Berkovsky et al. (2017)	User trust Big-Five traits	Personality neighborhood	FFM	TIPI-10	IMDb
50/50 (Nalmpantis and Tjortjis 2017)	User rating Big-Five traits	Personality neighborhood	FFM	IPIP-50	MovieLens
MBTI-CF (Yi et al. 2016)	MBTI personality types	Personality neighborhood	MBTI	MBTI	Webtoons
Sofia et al. (2016)	Friend rating Big-Five traits	Personality neighborhood	FFM	BFI-44	IMDb
Karumur and Konstan (2016)	Big-Five traits	Personality matching	FFM	IPIP-50	MovieLens
Potash and Rumshisky (2016)	Movie reviews Big-Five traits	Personality neighborhood	FFM	BFI-44	IMDb
Karumur et al. (2016)	Movie rating Big-Five traits	Personality matching	FFM	TIPI-10	MovieLens
Scott et al. (2016a)	User culture factor Big-Five traits	Personality matching	FFM	BFI-10	CP-QAE-I
Wang (2015)	Big-Five traits	Personality matching	FFM	TIPI-10	MovieLens
Wu and Chen (2015)	User demography User rating Big-Five traits	Personality neighborhood	FFM	IPIP-25	Yahoo! MovieHetRec
Golbeck and Norris (2013)	User rating Big-Five traits	Personality neighborhood	FFM	APR	Netflix
Wu et al. (2013)	User rating Big-Five traits	Personality matching	FFM	BFI-44	Douban
Odić et al. (2013)	Emotions Big-Five traits	Personality matching	FFM	BFI-44	LDOS-CoMoDa
Cantador et al. (2013)	Big-Five traits	Personality matching	FFM	IPIP-20	myPersonality
HappyMovie (Quijano-Sanchez et al. 2011)	TKI personality types Social trust User rating	Personality neighborhood	TKI	TKI test	Facebook
Hu and Pu (2011)	User rating Big-Five traits	Personality neighborhood	FFM	TIPI-10	MovieLens
Quijano-Sanchez et al. (2010)	Social trust Big-Five traits	Personality neighborhood	FFM	BFI-44	Self-collected
Recio-Garcia et al. (2009)	TKI personality types	Personality neighborhood	TKI	TKI test	MovieLens
Song et al. (2009)	MBTI personality types Emotions	Personalitymatching	MBTI	MBTI	Korean Film Council

compare recommendation accuracy with various combinations of feature sets. their results suggest that personality features contributed significantly to the improvement of recommendation accuracy, whereas physiological features contributed less. Cheng et al. (2016) introduced a hybrid method for personality-aware music recommendations. They used personality matching of the user's personality traits with an extracted feature from songs audio, and classify these features using support vector machine (SVM) algorithm. Their results suggest that combining the content and context information can reduce the MAE and improve the decision accuracy and prediction rate. While Schedl et al. (2016) studied the relationship between personality traits and classical music preferences, they grouped the users into four clusters based on the personality traits and tried to infer the preference of each cluster regarding classical music. The order of the visualizations for a given user is computed with respect to the ranking preferred by other users in the same cluster. Ferwerda et al. (2014) discussed the possibility to enhance music recommendation systems by incorporating the user's psychological factors such as emotional and personality states. The authors discussed how people listen to music to control their emotional states, and how this adjustment is related to their personality traits. They focused on the methods to acquire data from social media networks to estimate the current emotional state of the listeners. Finally, they discussed the connection of the accurate emotionally with the music categories to support the emotional adjustment of listeners. The same research group proposed a personality-aware music recommender system Ferwerda and Schedl (2016), where they employed the user's personality traits as a general model. The authors specified the relationships between listeners' personality and their behavior, preferences, and needs, in addition to that the authors studied the different ways to infer user's personality traits from user-generated data of social media websites (e.g., Facebook, Twitter, and Instagram). Hu et al. (2010a) proposed a general model that can deduce user's music preferences based on their personality characteristics. Their subject studies prove that most of the active users think that the recommended songs are more precise for their friends, however, these users enjoy more using personality questionnaires based recommenders for finding songs for themselves. The authors investigated if domain based knowledge has an impact on user's understanding of the system. They found that novice users, who are less knowledgeable about music, generally appreciated more personality based recommenders. Zhou et al. (2011) used decision trees to developed a heuristic personality-aware music recommendation system for niche market. To solve the cold start problem, instead of trying to improve the recommendation performance on new users by recommending the most popular songs, their proposed system directly associates the personality of new users with the most suitable items. Gupta et al. (2020) proposed a personality-aware music recommender system that automatically predicts the listener's personality and recommend the songs relevant to the listener's dominant personality trait. Melchiorre et al. (2020) investigated the correlation between personality traits and musical preferences at the fine-grained content level. Specifically they analyzed the listening patters of 1300 Last.fm users and identified several significant medium and weak correlations between personality traits and music audio features. Bansal et al. (2020) studied the relationship between genre exclusivity and Big-Five personality traits, their main findings suggest that listeners with high score of openness personality trait prefer jazz and folk music, and are less interested in pop music. Kouki et al. (2020) studied the benefits of explanations for hybrid recommender systems including personality-aware recommendation systems. They performed a crowd-sourced user study where the system generates personalized recommendations and explanations for real users of the Last.fm music platform. Table 8 summarizes the literature of personality-aware music recommendation systems.

4.4 Photo recommendation

Associating images features and personality traits is twofold: known the feature of the image can help to infer the personality of users who interact with the image, and know the personality traits of the users could help to recommend relevant images. Guntuku et al. (2015b) studied methods for modeling the personality character of users based on a collection of images that they tagged as 'favorite' on Flickr. Their study presents several methods for enhancing personality detection performance by proposing better features and modeling approaches. They evaluated their approach by measuring its efficiency when used in an image recommendation system. Their Personality prediction method is divided into two stages, firstly transforming the features to answers (F2A) and then mapping the answers to personality trait scores (A2P). The presented results showed the need for using high-level user understandable features and illustrate the effectiveness of a A2P and F2A approach compared to the traditional F2P (Features-to-Personality) method that is usually used by existing works. While in Guntuku et al. (2015a) they studied the effects of personality (Big-Five Model) and cultural traits (Hofstede Model) on the potency of multimedia-stimulated positive and negative emotions. They compared three multilevel regression: (1) a baseline model that only considers system factors, (2) an extended model that includes personality and culture; (3) an optimistic model in which each participant is modeled. Their analysis proves that personal and cultural traits represent 5.6% of the variance in positive affect and 13.6% of the variance in negative affect. Furthermore, the affect-enjoyment correlation varied across the clips, which proves that personality and culture have a key role in predicting the intensity of negative affect and enjoyed level. Li et al. (2019) developed an end-to-end personality driven multi-task deep-learning-based image aesthetic model that employs the user's personality traits for image aesthetic rating. Both image aesthetics and personality traits are learned from the proposed multi-task deep-learning model. The personality features are used to represent the aesthetics features, hence, producing the optimal generic image aesthetics scores. Furthermore, in Li et al. (2020) they extended their method to offer a personality-aware multi-task framework for generic as well as personalized image aesthetics assessment. They introduced a framework that predicts the aesthetics distribution of an image and the Big-Five personality traits of people who like the image. In the proposed framework, the generic aesthetics score of the image are computed based on the predicted aesthetics distribution. To capture the common representation of generic image aesthetics and user'ss personality traits, and a Siamese network is trained using aesthetics data and personality data jointly. Gelli et al. (2017) investigated the effects of personality on user behaviors with images in a social media, and which visual stimuli contained in photo content can affect user behaviors. They analyzed a twitter dataset of 1.6 million user and image retweet behaviors. Their statistical analysis show a significant correlation between personality traits and affective visual concepts in image content. Kim et al. (2019) studied the relationships between Instagram user personality traits and color features of their photos, and found that agreeableness is the most relevant trait that is associated with the photo and color features, and neuroticism personality trait was negatively correlated with the color harmony of their photos, extraversion personality trait was positively associated with the color diversity, whereas openness was negatively associated with the color diversity and color harmony of their photos. He et al. (2020) proposed a psychological preference inference engine for personalized face recommendation named DiscoStyle. Specifically, they used transfer learning for identity

Table 8 Personality-aware music recommendation systems

System	Factors	Technique	Model	Test	Dataset
Moscato et al. (2020)	User mood Big-Five traits	Deep-learning	FFM	TIPI-10	Deezer myPersonality PsychoFlickr
Melchiorre and Schedl (2020)	Music preferences Big-Five traits	Personality matching	FFM	TIPI-10	Last.fm myPersonality
Kouki et al. (2020)	Music preferences Big-Five traits	Personality matching	FFM	APR	Last.fm
Bansal et al. (2020)	Music preferences Big-Five traits	Personality matching	FFM	APR	Nokia DB
Liu and Hu (2020)	Music preferences Big-Five traits	Deep-learning	FFM	TIPI-10	Self-collected
Gupta et al. (2020)	User rating Big-Fivetraits	Personality matching	FFM	APR	Last.FM
PTOC_CF Sun et al. (2018)	Big-Five traits	Personality neighborhood	FFM	TIPI-10	Last.fm myPersonality
Kleć (2017)	MBTI personality types	Personality matching	MBTI	MBTI-60	Self-collected
Ferwerda et al. (2017a)	Big-Five traits	Personality matching	FFM	TIPI-10	myPersonality Last.fm
Ferwerda et al. (2017b)	Big-Five traits	Personality matching	FFM	TIPI-10	myPersonality Last.fm
Onori et al. (2016)	Big-Five traits	Personality neighborhood	FFM	TIPI-10	myPersonality Last.fm
Ferwerda and Schedl (2016)	Behaviors Big-Five traits	Personality matching	FFM	APR	Facebook Twitter
Ferwerda et al. (2016)	Big-Five traits	Personality matching	FFM	BFI-44	LFM-1b (Last.fm)
Cheng and Tang (2016)	User rating Big-Five traits	Personality matching	FFM	BFI-44	Self-collected
Schedl et al. (2016)	Big-Five traits	Personality neighborhood	FFM	BFI-44	Self-collected
(Ferwerda and Schedl 2014)	Emotional state Big-Five traits	Personality matching	FFM	APR	Twitter Last.FM
Zhou et al. (2011)	Item popularity Big-Five traits	Personality neighborhood	FFM	TIPI-10	MovieLens
Hu and Pu (2010a)	User demography User rating Big-Five traits	Personality neighborhood	FFM	TIPI-10	Last.FM
Hu and Pu (2010b)	User rating Big-Five traits	Personality neighborhood	FFM	TIPI-10	Last.FM
Hu (2010)	Big-Five traits	Personality neighborhood	FFM	APR	N/A

related facial feature representation to personality preference related facial feature. Scott et al. (2016b) compared three statistical models to study the influence of personality and cultural traits on perception of multimedia quality, the first system only consider system factors, the second the model to include personality traits and culture factors, and the their is personalized to model each participants. Their findings suggest that personality and cultural traits represent 9.3% of the variance attributable to human factors on perception of multimedia quality. Table 9 summarizes the literature of personality-aware photo recommendation systems.

4.5 Academic recommendations

Many works have used personality traits for academic-oriented recommendation systems, such as courses recommendations, conference attendee recommendations and research paper recommendations. Xie 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 proportions of the past and present 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. Qamhieh et al. (2020) proposed a personality-aware career recommendation system named Personalized Career-path Recommender System (PCRS), PCRS to provide recommendation to help high school students choose engineering discipline. PCRS leverages the students' personality type, academic performance and extra-curricular skills, these information are inputted to fuzzy intelligence model of N-layered architecture. They evaluated PCRS performance using a sample 1250 engineering students enrolled in 7 engineering disciplines at An-Najah National University. Similarly, Asabere et al. (2018) proposed a recommendation algorithm for conference attendees called PerSAR (Personality-Socially-Aware-Recommender). The proposed system is based on a hybrid approach of social relations and personality characters of the conference participants. To evaluate their proposed system, the authors used the dataset of The International Conference on Web-Based Learning (ICWL) 2012, which includes the social ties of 78 conference participants with a total time-frame of 12 hours (720 minutes). Uddin et al. (2016) Proposed a personality-aware framework named PBRE to improve academic choice for newly enrolled students. Their proposed framework makes use of the research field of Predicting Educational Relevance For an Efficient Classification of Talent (PERFECT Algorithm Engine), which uses stochastic probability distribution modeling to help the student to choose the relevant academic field. Hariadi et el (2017) proposed a personality-aware book recommendation system that combines the user's attributes as well as his personality traits. The proposed system leverages MSV-MSL (Most Similar Visited Material to the Most Similar Learner) method to compute the similarity between users and form the personality neighborhood. Zhang et al. (2019) investigated and summarized different methods that leverage personality traits in collaborative personalized recommendations. They extended an existing personality-aware recommendation system and proposed two other alternative recommendation systems which take advantage of the personality traits to enhance learning content

Table 9 Personality-aware photo recommendation systems

System	Factors	Technique	Model	Test	Dataset
DiscoStyle (He et al. 2020)	Facial features psychological preference	Deep-learning	FFM	APR	StyleFace
Li et al. (2019)	Image aesthetic rating Big-Five traits	Deep-learning	FFM	BIF-10	PsychoFlickr AADB
Li et al. (2020)	Image aesthetic rating Big-Five traits	Deep-learning	FFM	BIF-10	PsychoFlickr FLICKR-AES
Kim and Kim (2019)	Image aesthetic choice Big-Five traits	Personality matching	FFM	BFI-44	Self-collected
Gelli et al. (2017)	User behaviors Big-Five traits	Personality matching	FFM	APR	Twitter
Scott et al. (2016b)	Culture factors Big-Five traits	Deep-learning	FFM	BFI-10	Self-collected
Guntuku et al. (2015b)	User culture factor User rating Big-Five traits	Personality neighborhood	FFM	BFI-10	PsychoFlickr
Guntuku et al. (2015a)	cultural traits Big-Five traits	Personality matching	FFM	BFI-10	CP-QAE-I

recommendation. Table 10 summarizes the literature of personality-aware academic recommendation systems.

4.6 Product recommendations

Dhelim et al. (2020b) introduced Meta-Interest, a personality-aware product recommendation system that considers the user interests and personality traits and recommends relevant products by exploring the possible user-item metapaths. Meta-Interest is personality-aware from two aspects; it includes the user's personality traits to predict his/her topics of interest and to match the user's personality facets with the associated products. Tkalcic et al. (2010) proposed a new approach for measuring the user similarity for collaborative filtering recommender systems that is based on the Big-Five personality model in the context of product recommendation. Buettner (2017) introduced a personality-aware framework for product recommender named PBPR. The proposed framework analyzes the user's social media profile to infer its personality traits and recommend products accordingly. The author evaluated his proposed framework as IT artefact using a dataset from XING. The results indicates that (i) the user's personality can be predicted from social media data with predictive gain between 23.2% and 41.8% and (ii) personality-aware products product recommendation can be improved by a predictive gain of 45.1%. Huang et al. (2020), used a data driven method to predict online shoppers' online buying preferences. Firstly, the authors used text mining method based on the shoppers' language usage behaviors to create seven different dimension lifestyle-lexicons. Following that, they included these lifestyle-lexicons in the product recommendation system that can predict the shoppers' buying preferences. Roffo (2016) discussed utilizing personality to compute the association between the shopper's purchasing tendency and the advert's recommendations. Moreover, the author introduced the ADS dataset, an advertising benchmark enriched with Big-Five personality traits of users along with 1200 personal photos, while in (Roffo and Vinciarelli 2016) they used the same dataset to study unique associations among the consumer's buying tendency and advert personality-aware recommendations. Adamopoulos and Todri (2015) used a dataset from Amazon.com to evaluate a personality based recommendation, they have inferred the user's personality traits along with their needs and other contextual information from their social media profiles. Their findings is that adding personality to the recommendation process can increase the efficiency of the system. Table 11 summarizes the literature of personality-aware product recommendation systems.

4.7 Game recommendations

Yang et al. (2019) introduced a personality-aware game recommendation system, they apply text mining on the players' social network posts to extract their personality types and analyzed the games' content to associate these games with certain personality types. They proved the effectiveness of their proposed system through an experiment on 63 players and more than 2000 games. Lima et al. (2018) designed a new method for interactive storytelling in games, in which the quests and the ongoing story follow the view of individual personality traits and behaviors in a non-deterministic way. They trained an artificial neural network to predict player behaviors in real-time, allowing planning operators to use personality traits and player behaviors as logical terms in their preconditions. Chan et al. (2018) proposed a method for matching players using personality types to augment the enjoyment and social interaction in exergames. They argue that maintaining high levels of enjoyment

Table 10 Personality-aware academic recommendation systems

System	Factors	Technique	Model	Test	Dataset
PCRS (Qamhieh et al. 2020)	MBTI personality types Academic performance Extra-curricular skills	Deep-learning	MBTI	MBTI	Self-collected
Zheng and Subramaniyan (2019)	Course rating Big-Five traits	Matrix factorization	FFM	TIPI-10	Self-collected
Sun et al. (2020)	Big-Five traits	Matrix factorization	FFM	IPIP	mypersonality
PerSAR Asabere et al. (2018)	Social characteristic Big-Five traits	Personality neighborhood	FFM	APR	ICWL 2012
SPARP (Xia et al. 2017)	Social characteristic Big-Five traits	Personality neighborhood	FFM	APR	ICWL 2012
Hariadi and Nurjanah (2017)	User attributes Big-Five traits	Personality neighborhood	FFM	APR	Amazon
PBRE (Uddin and Banerjee 2016)	Academics background Big-Five traits	personality matching	FFM	APR	Facebook Twitter LinkedIn
Fernández-Tobías et al. (2016)	Book likes Big-Five traits	Matrix factorization	FFM	IPIP	mypersonality
Fernández-Tobías and Cantador (2015)	Book likes Big-Five traits	Personality neighborhood	FFM	IPIP	mypersonality
Fernández-Tobías and Cantador (2014)	Book likes Big-Five traits	Matrix factorization	FFM	IPIP	mypersonality

Table 11 Personality-aware product recommendation systems

System	Factors	Technique	Model	Test	Dataset
Meta-Interest (Dhelim et al. 2020b)	User interest User rating Big-Five traits	Hybrid personality filtering	FFM	TIPI-10	Newsfullness
Dhelim et al. (2020a)	User interest Big-Five traits	Personality neighborhood	FFM	TIPI-10	Newsfullness
Aguiar et al. (2020)	Needs Values Big-Five traits	Personality neighborhood	FFM	APR (IBM)	Amazon
Khodabandehlou et al. (2020)	Product rating Big-Five traits	Personality neighborhood	FFM	NEO-PI-60	Self-collected
Yakhchi et al. (2020)	Product rating Big-Five traits	Matrix factorization	FFM	APR (LIWC)	Amazon
PBPR Buettner (2017)	User rating Big-Five traits	Personality matching	FFM	TIPI-10	XING
Roffo (2016)	User rating Big-Five traits	Matrix factorization	FFM	BFI-10	ADS
Roffo and Vinciarelli (2016)	Big-Five traits	Personality matching	FFM	BFI-10	ADS
Adamopoulos and Todri (2015)	User rating Big-Five traits	Matrix factorization	FFM	APR	Amazon
Hu and Pu (2014)	Big-Five traits	Personality matching	FFM	California Q-set	Self-collected
Elahi et al. (2013)	Needs Values Big-Five traits	Matrix factorization	FFM	APR	Amazon
Tkalcic et al. (2010)	User rating Big-Five traits	Hybrid personality filtering	FFM	IPIP-50	IAPS
Huang et al. (2020)	User reviews Big-Five traits	Personality matching	FFM	APR	Amazon

and active social interactions is crucial because both can offer retention and continuation of gameplay and exercise involvement. Their results suggest that there was a strong reliability between players pairs with dominant extraversion and openness traits, and poor reliability between player pairs with dominant conscientiousness and openness traits. Hill et al. (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. The results suggested that extraversions have a moderate association with the socializer gaming preference, and a weak association with the daredevil gaming preference. While Abbasi et al. (2020) discussed the personality differences between gamers and non-gamers. Supported by evidence obtained by analyzing the personality types of 855 students (gamers and non-gamers), they concluded that gamers have a personality types that is significantly different on compared to non-gamers. Yang et al (2017) tried to measure the player's personality traits and utilize that information to recommend relevant games. The player's personality traits is measured by applying a text mining technique on textual contents posted by the player. The same method is used on the games' comments to measure the games' personality traits. Table 12 summarizes the literature of personality-aware game recommendation systems.

4.8 Points of interest recommendations

Chi-Seo et al. (2020) introduced a system that employs deep learning to classify and recommend tourism types that are compatible with the user's personality. The model is composed out of three layers, each layer incorporates a service provisioning layer that real users face, the recommendation service layer, responsible to produce recommended services based on user information inputted, and the adaptive definition layer, that learns the types of tourism that fit for the user's personality types. Wang et al. (2020) proposed a trust-based POI recommendation system, they leverage the personality similarity between users to compute the trust level. In addition to trust and personality information, they also make use of the graphic and temporal influence in the recommendation model. Zhang et al. (2018) introduced a new POI recommendation system that uses POI classification model named POIC-ELM. POIC-ELM extracts 9 features that are related to 3 factors, the user's personality information the POI information and the user's social relationships information. The learned feature are then fed to an extreme learning machine (ELM) for POI classification. Braunhofer et al. (2014a) introduced STS (South Tyrol Suggests), a personality-aware POI recommender system that uses an active learning module and personality-aware matrix factorization recommendation to infer the relevant POI. In the same vein, in Braunhofer et al. (2014b) they designed a personalized active learning method that takes advantage of the user's personality information to get more accurate in-context POI ratings. Their result shows that using personality information in active learning yield better accuracy for POI recommendation. Tanasescu et al. (2013) introduced the concept of 'personality of a venue'. They extracted keywords and other annotations from the reviews of the venues and mapped these information to Big-Five personality traits. The experimental testing confirmed the correlation between visitor's personality traits and the personality of the visited venue. Sertkan et al. (2019) proposed an automatic method for computing the Seven-Factor equivalent of tourism sites. Regression analysis, cluster analysis, and exploratory data analysis are performed to find the correlation between Seven-Factors and the type of tourist destination site. Feng et al. (2013) fused three factors, mainly interpersonal

Table 12 Personality-aware game recommendation systems

System	Factors	Technique	Model	Test	Dataset
Abbasi et al. (2020)	Gaming preferences HEXACO traits	Personality matching	HEXACO	HEXACO-60	Self-collected
Yang and Huang (2019)	Game rating Big-Five traits	Hybrid personality filtering	FFM	APR	Steam
de Lima et al. (2018)	User behaviors Big-Five traits	Deep-learning	FFM	BFI-10	N/A
Chan et al. (2018)	Player enjoyment Social factor Big-Five traits	personality matching	FFM	TIPI-10	Self-collected
Yang et al. (2017)	Big-Five traits	Personality matching	FFM	APR	Steam
Zeigler-Hill and Monica (2015)	Gaming preferences HEXACO traits	Personality matching	HEXACO	HEXACO-60	Steam

interest similarity, personal interest similarity and interpersonal influence to implement probabilistic matrix factorization for personality-aware recommendations. They concluded that personal interest factor can enhance the user's individualities in the recommendation system. Ting et al. (2018) proposed a personality-aware job recommendation system to compute personality features from user-generated content in Facebook. They created a prediction model that uses computational score for job recommendations that match the user's personality. The accuracy of the proposed personality-aware job recommendation system is 93.1%. Table 13 summarizes the literature of personality-aware POI recommendation systems.

5 Datasets and Benchmarks

Due to the availability of open public datasets that considered the user's personality information, many personality-aware recommendation systems were able to train their proposed models and compare them using the state-of-the-art benchmarks. In this section, we present some of the widely used personality datasets in the context of personality-aware recommendation systems.

myPersonality dataset: In 2007, David Stillwell a PhD student at the University of Nottingham designed a Facebook application called myPersonality that leverages IPIP version of the NEO personality inventory personality questionnaire and displays the personality score instantly (Stillwell and Kosinski 2014). myPersonality was initially intended for limited use, David shared it with his close friends. Later on, surprisingly the number of users who joined the study increased dramatically, and many users were willing to donate their data to be used for academic purposes. By 2012, more than 6 million users finished the IPIP personality questionnaire, and the respondents came from different age groups, backgrounds and cultures. myPersonality dataset was anonymized and samples of it were shared with many researchers. In 2018, the creators of myPersonality decided to stop the project, as it has become extremely challenging to maintain the dataset with the increasing number of usage requests from researchers over the last few years.

MovieLens dataset: MovieLens is a widely used open dataset in recommendation system researches. It contains movie rating data extracted from the famous movie recommendation and rating website MovieLens.com (Harper and Konstan 2016). The ratings were collected over different periods of time, there are many available versions of the dataset depending on the size of the dataset. The largest available version of the dataset is named MovieLens 25M. It contains 25 million movie ratings and one million tag applications applied to 62,000 movies by 162,000 users. Personality2018 (Nguyen et al. 2018) is a version of MovieLens dataset that includes the personality information of the users that rated the movies according to their levels of diversity, popularity, and serendipity, Personality2018 also includes the TIPI score of 1834 users along with the movie rating that were given by these users, and it is available for public download.

Newsfullness dataset: Newsfullness is a news sharing platform that uses personality-aware recommendation for of news articles (Dhelim et al. 2020a). Newsfullness contains TIPI scores of more than 2228 users along with their articles that these users viewed or liked. The collected articles were from all the main news websites, such as BBC, CNN, RA and Aljazeera, from different news categories (business, politics, health, sports, travel, entertainment, art, education, science and technology).

Table 13 Personality-aware POI recommendation systems

System	Factors	Technique	Model	Test	Dataset
Jeong et al. (2020)	MBTI personality types	Deep-learning	FFM	MBTI	N/A
Wang et al. (2020)	Trust level Big-Five traits	Personality neighborhood	FFM	APR	LBSN dataset
Alves et al. (2020)	Big-Five traits	Personality matching	FFM	BFI-44	Self-collected
Sertkan et al. (2019)	Tourist preferences Big-Five traits	Personality matching	FFM	APR	Self-collected
Zhang et al. (2018)	Location Big-Five traits	Deep-learning	FFM	APR	Foursquar Brightkit Gowall
Yusefi Hafshejani et al. (2018)	User rating Big-Five traits	Personality neighborhood	FFM	NEO-FFI-60	STS
Ting and Varathan (2018)	Big-Five traits	Personality matching	FFM	BFI-44	Facebook
Braunhofer et al. (2015)	Demographic attributes Big-Five traits	Matrix factorization	FFM	FIPI-5	STS
STS Braunhofer et al. (2014a)	Context rating Big-Five traits	Matrix factorization	FFM	TIPI-10	STS
Braunhofer et al. (2014b)	Context information Big-Five traits	Personality neighborhood	FFM	TIPI-10	Self-collected
Tanasescu et al. (2013)	Venue rating Big-Five traits	Personality matching	FFM	APR	Self-collected
Feng and Qian (2013)	interpersonal interest personal interest interpersonal influence Big-Five traits	Matrix factorization	FFM	APR	Yelp
Elahi et al. (2013)	POI rating Big-Five traits	Matrix factorization	FFM	TIPI-10	Self-collected

ADS dataset: ADS Dataset is a publicly available benchmark for computational advertising enriched with the user's Big-Five personality traits and 1,200 personal user's pictures. ADS benchmark allows two main tasks: rating prediction over 300 real advertisements (i.e., Rich Media Ads, Image Ads, Text Ads) and click-through rate prediction. Table 14 summarizes the above-mentioned datasets.

6 Challenges and open issues

Although that personality-aware recommendation system offers many advantages and solutions to tackle recommendation challenges that conventional recommendation systems cannot solve, such as cold start and recommendation diversity. However, using the user's personality in the recommendation bring up new challenges and ethical issues, in this section we discuss some of these challenges.

6.1 Measurement accuracy

The accuracy of the personality measurement is vital for personality-aware recommendation system, the inaccurate measurement of the user personality traits will inevitably lead to inaccurate recommendations. What makes things worse is that the system considers personality traits as content information that do not need update frequently, and will offer inaccurate information all the time. The personality questionnaire contains questions that are relative to the subject itself, and there is no standard measurement of the questioned features, which could increase the reference-group effect. For instance, an introverted subject may identify himself as an extrovert, even if he filled the questionnaire correctly, that is because all his close friends are also introverts, therefore his judgment was relative to his environment. APR methods may also inaccurately detect the user's personality for various reasons, for example, image-based APR might predict the personality of a user by analyzing his shared photos on social media without considering the context of these photos. For example, a user who shares nature photos frequently as a part of his job as a photographer or a war photo shared by a journalist may not reflect their personalities. To avoid this problem, the recommendation system should not take the personality information as granted, and must verify the correctness of such information by frequently measuring the personality preferences of the user. One way to do that is by comparing the preferences of the user with other users and optimize its personality neighborhood over the time.

6.2 Personality information privacy

The privacy of the user's personality poses a new challenge in addition to the existing challenge of preserving the privacy of user's information. As the user's personality information is even more sensitive than other information in the user's profile. In March 2018, Facebook-Cambridge Analytica scandal has drawn the attention of the world. A Facebook application created by the a data analytic company named Cambridge Analytica unrightfully collected the personality information of more than 87 million users, aiming to manipulate their voting choice in the 2016 US presidential election (Hinds et al. 2020). The challenge of personality-aware recommendation system is to preserve the personality information of the users. The recommendation system should collect only the necessary personality information required to enhance the recommendation, in this regard, one of the

Table 14 Personality datasets

Dataset	Domain	Content description	Availability
MovieLens	Movies	user's Big-Five scores and their rating to movies.	Available for public download (https://grouplens.org/datasets/personality-2018/)
myPersonality	User profiles	Facebook profiles and their Big-Five scores	Discontinued since April 2018 (https://www.psychometrics.cam.ac.uk/productsservices/mypersonality)
ADS	Products	Consists of 300 real advertisements rated by 120 users, enriched with user's Big-Five personality traits and 1,200 personal user's pictures.	Available for public download (https://www.kaggle.com/groffo/ads16-dataset)
PsychoFlickr	Images	Consists of 60k images, 200 favorite images for each of the 300 users along with their Big-five personality traits	Available for public download (http://vips.sci.univr.it/dataset/psychoflickr/)
Newsfullness	News articles	User's Big-Five scores and their news articles viewing history	Available for researchers (www.newsfullness.live/dataset)
Last.fm	Music	Consists of two kinds of data at the song level: tags and similar songs. Usually combined with other dataset that contains user's personality information.	Available for public download (http://millionsongdataset.com/lastfm/)
IMDb	Movies	Contain user's ratings and movies information, usually combined with other dataset that contains user's personality information.	Can be obtained through the official API (https://developer.imdb.com/)
Twitter	Friendships	Contain user's tweets and follower networks, usually the tweets are further processed with APR API to extract the user's personality information	Can be obtained through the official API (https://developer.twitter.com)

solution is to user short personality questionnaire, such as TIPI-10, that have been proven to be as effective as long questionnaires, hence, the privacy risk is minimized, as the user is required to reveal only the minimum required information.

7 Conclusion

To the best of our knowledge, this survey is the first that focuses on personality-aware recommendation system. We have reviewed the literature of the recent works in this domain, and show the main differences between different works, in terms of personality model, as well as in terms of the used recommendation technique. The vast majority of personality-aware recommendation systems leverage Big-Five personality model to represent the user's personality. Personality-aware recommendation systems have the upper hand when compared with the conventional recommendation techniques, especially when dealing with cold start and data sparsity problems. However, with the understanding of the user's personality advantage comes the challenge of preserving the privacy of the user personality information, and also the challenge of maintaining a high personality detection accuracy.

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Declarations

Conflicts of interest The authors declare that they have no conflict of interest.

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