Personality and Recommender Systems

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1 Introduction

As argued in Chapter "Individual and Group Decision Making and Recommender Systems", an important function of recommender systems is to help people make better decisions. It has also been found that an improvement in the rating prediction accuracy (usually measured with metrics such as RMSE, see also Chapter "Evaluating Recommender Systems") does not necessarily mean a better user experience [64]. Furthermore, assessing the recommender systems from a user-centric perspective (e.g., decision confidence and system satisfaction) yields a better picture of the quality of the recommender system under study. Hence, one should better take into consideration user characteristics for optimizing a recommender system. This is why personality, which plays an important role in decision-making [22], has been considered to improve the system.

From its definition in psychology, personality accounts for the individual differences in our enduring emotional, interpersonal, experiential, attitudinal, and motivational styles [48]. Incorporating these differences in the recommender system appears to be a promising choice for delivering personalized recommendations. Furthermore, personality parameters can be quantified as feature vectors, which makes them suitable to use in computer algorithms. Therefore, user personality has been considered in a wide range of aspects of recommender systems. For example, personality has been used to improve user-user similarity calculation in solving the

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new user problem [44, 97]. It has also been demonstrated that people with different personalities can be more or less inclined to consume novel items, so the degree of diversity in presenting recommended items can be personalized accordingly [102]. Moreover, group modeling based on personality has improved the performance of group recommendations [52, 75, 77]. Indeed, recently the topic of using personality for personalization has gained traction not only in individual research done but also in a dedicated edited volume [94] and tutorials at the RecSys conference [69, 93].

However, the acquisition of personality factors for individual users has been mainly done through extensive questionnaires, which was an obstacle in a day-to-day use of recommender systems. Examples of such questionnaires are the International Personality Item Pool (IPIP) [38] and the NEO Personality Inventory [62]. In recent years, several investigations have been conducted to extract personality parameters using machine learning techniques [37, 53, 74]. Valuable sources for detecting the personality of a user without bothering her/him with extensive questionnaires are social media streams (e.g., Facebook [53], blogs [47], Instagram [32], Twitter [74]) and other user-generated data streams (e.g., email [85], drug consumption [35], eye gaze [8]).

In this chapter, we survey the usage of the psychological model of personality to improve recommendation accuracy, diversity, to address the new user problem, to improve cross-domain recommendations, and in group recommendation scenarios. We focus on the tools needed to design such systems, especially on (i) personality acquisition methods and on (ii) strategies for using personality in recommender systems. The chapter is organized as follows. In Sect. 2 we survey various models of personality that were developed and are suitable for recommender systems. In Sect. 3 we present various methods for acquiring personality, which fall in either of the two categories: *implicit* or *explicit*. In Sect. 4 we discuss various strategies that exploit personality and have been used so far in recommender systems. Further, in Sect. 5 we present the challenges that are still ahead in this area. Finally we provide some conclusive thoughts in Sect. 6.

2 Personality Model

According to [63], personality accounts for the most important dimensions in which individuals differ in their enduring emotional, interpersonal, experiential, attitudinal, and motivational styles. Translated into the recommender systems terminology, personality can be thought of as a (component of) user profile, which is context-independent (it does not change with time, location or some other contexts—see Chapter “Context-Aware Recommender Systems: From Foundations to Recent Developments” for context in recommender systems) and domain-independent (it does not change through different domains, e.g., books, movies—see also Chapter “Design and Evaluation of Cross-domain Recommender Systems” for personality in cross-domain recommender systems).

Table 1 Examples of adjectives related to the FFM [63]

Factor	Adjectives
Openness (O)	Artistic, curious, imaginative, insightful, original, wide interest
Conscientiousness (C)	Efficient, organized, planful, reliable, responsible, thorough
Extraversion (E)	Active, assertive, energetic, enthusiastic, outgoing, talkative
Agreeableness (A)	Appreciative, forgiving, generous, kind, sympathetic, trusting
Neuroticism (N)	Anxious, self-pitying, tense, touchy, unstable, worrying

Historically, the first reports of studies of individual traits among humans go back to the ancient Greeks with the Hippocrates' Four Humours that eventually led to the personality theory known today as the four temperaments (i.e., Choleric, Sanguine, Melancholic and Phlegmatic) [50].

Today, the Five Factor Model of personality (FFM) [63] is considered one of the most comprehensive and the widely used personality models in recommender systems [15, 27, 43–45, 69, 70, 90, 99, 102]. The FFM is sometimes referred to also as the Big-Five (Big5) model of personality.

2.1 The Five Factor Model of Personality

The roots of the FFM lie in the lexical hypothesis, which states that things that are most important in people's lives eventually become part of their language. Studying the usage of language, researchers extracted a set of adjectives that describe permanent traits (see Table 1). With further research, these adjectives were clustered into the five main dimensions: Openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (the acronym OCEAN is often used) [63].

Openness to Experience (O), often referred to just as Openness, describes the distinction between imaginative, creative people and down-to-earth, conventional people. High O scorers are typically individualistic, non-conforming and are very aware of their feelings. They can easily think in abstraction. People with low O values tend to have common interests. They prefer simple and straightforward thinking over complex, ambiguous and subtle. The sub-factors are imagination, artistic interest, emotionality, adventurousness, intellect, and liberalism.

Conscientiousness (C) concerns the way in which we control, regulate and direct our impulses. People with high C values tend to be prudent while those with low values tend to be impulsive. The sub-factors are self-efficacy, orderliness, dutifulness, achievement-striving, self-discipline, and cautiousness.

Extraversion (E) tells the degree of engagement with the external world (in case of high values) or the lack of it (low values). The sub-factors of E are friendliness, gregariousness, assertiveness, activity level, excitement-seeking, and cheerfulness. Extrovert people (high score on the E factor) tend to react with enthusiasm and often have positive emotions, while introverted people (low score on the E factor) tend to be quiet, low-key and disengaged in social interactions.

Agreeableness (A) reflects individual differences concerning cooperation and social harmony. The sub-factors of A are trust, morality, altruism, cooperation, modesty, and sympathy.

Neuroticism (N) refers to the tendency of experiencing negative feelings. People with high N values are emotionally reactive. They tend to respond emotionally to relatively neutral stimuli. They are often in a bad mood, which strongly affects their thinking and decision making (see Chapter "Individual and Group Decision Making and Recommender Systems" for more on decision making). Low N scorers are calm, emotionally stable, and free from persistent bad mood. The sub-factors are anxiety, anger, depression, self-consciousness, immoderation, and vulnerability. The neuroticism factor is sometimes referred to as emotional stability [40].

2.2 Other Models of Personality

Other personality models that can be of interest to the recommender system community are the vocational RIASEC (with the main types *realistic, investigative, artistic, social, enterprising*, and *conventional*) model [42], which was used in an e-commerce prototype [10]; and the Bartle model (with the main types *killers, achievers, explorers* and *socializers*), which is suitable for the videogames domain [88].

The Thomas-Kilmann conflict mode personality model has been developed to model group dynamics [89]. The model is composed of the following two dimensions that account for differences in individual behaviour in conflict situations:[1] *assertiveness* and *cooperativeness*. Within this two-dimensional space, subjects are classified into any of these five categories: *competing, collaborating, compromising, avoiding*, or *accommodating*.

Although learning styles per se are not considered as a personality model, they share with personality the quality of being time invariant. In the domain of e-learning, models of learning styles have been used to recommend course materials to students [26]. An example is the Felder and Silverman Learning Style Model [30], which measures four factors: *active/reflective, sensing/intuitive, visual/verbal*, and *sequential/global*.

In addition, some ad-hoc personality models have been proposed in the recommender systems community. For a trendy pictures recommender system, a personality model with two types, the *trend-setters* and the *trend-spotters*, has been proposed, along with a methodology for predicting the personality types from social media networks [84]. Especially in the domain of social networks, there

[1] The Thomas-Kilmann conflict mode instrument is available at http://cmpresolutions.co.uk/wp-content/uploads/2011/04/Thomas-Kilman-conflict-instrument-questionaire.pdf.

Table 2 Main personality models

Ref.	Model name	Primary domain	Main types/traits
[63]	Five Factor Model	General	Openness, conscientiousness, extraversion, agreeableness, and neuroticism
[50]	Four temperaments	General	Choleric, Sanguine, Melancholic, and Phlegmatic
[42]	RIASEC	Vocational	Realistic, investigative, artistic, social, enterprising, and conventional
[88]	Bartle types	Video games	Killers, achievers, explorers, and socializers
[30]	Felder and Silverman Learning Style Model	Learning styles	Active/reflective, sensing/intuitive, visual/verbal, and sequential/global
[89]	Thomas-Kilmann conflict model	Group/conflict modeling	Assertiveness, cooperativeness

is a tendency to stress the *influence/susceptibility* aspects of users as the main personality traits (e.g., *leaders/followers*) [5] (Table 2).

2.3 Relationship Between Personality and User Preferences

A number of studies showed that personality relates strongly with user preferences. Users with different personalities tend to prefer different kinds of content. These relations are domain dependent. Such an information is very valuable when designing a recommender system for a specific domain.

In their study, Rentfrow and Gosling [79] explored how music preferences are related to personality in terms of the FFM model. They categorized music pieces each into one of the four categories: reflective & complex, intense & rebelious, upbeat & conventional, and energetic & rhythmic. The reflective & complex category is related to openness to new experience. Similarly, the intense & rebelious category is also positively related to openness to new experience. However, although this category contains music with negative emotions, it is not related to neuroticism or agreeableness. The upbeat & conventional category was found to be positively related with extraversion, agreeableness, and conscientiousness. Finally, they found that the energetic & rhythmic category is related to extraversion and agreeableness.

The relation between music and personality was also explored by Rawlings et al. [76]. They observed that the extraversion and openness factors are the only ones that explain the variance in the music preferences. Subjects with high openness tend to prefer diverse music styles. Extraversion, on the other hand, was found to be strongly related to preferences for popular music.

Manolios et al. [58] explored the relationship between personal values and user preferences in the music domain. The user preferences were not coded as is usual (e.g., preferences for genres or artists) but as relationships between values, consequences and attributes. Examples of these relationships are the value of conservation is strongly related to the consequence of relaxation, which is strongly related to the attribute emotions; or the value of openness to change is strongly related to the consequence of discovery/stimulation, which is strongly related to the attribute of complexity/originality.

Being different from the above work that focused on studying the effect of personality on user preferences for music genres or styles, Melchiorre and Schedl [65] analyzed its correlations with music audio features. The results show that most of correlations are low to medium, with the strongest effects for the openness trait.

Rentfrow et al. [78] extended the domain to general entertainment, which includes music, books, magazines, films, and TV shows. They categorized the content into the following categories: aesthetic, cerebral, communal, dark, and thrilling. The communal category is positively related to extraversion, agreeableness, and conscientiousness, while being negatively related to extraversion and neuroticism. The aesthetic category is positively related to agreeableness, extraversion and negatively to neuroticism. The dark category is positively related extraversion and negatively to conscientiousness and agreeableness. The cerebral category is related to extraversion, while the thrilling category does not reveal any consistent correlation with personality factors. Cantador et al. [14] also presented the results of an experiment over multiple domains including movies, TV shows, music, and books, based on the myPersonality dataset [53].

In another work [103], the authors surveyed 1706 users on Douban Interest Group,[2] which is a popular Chinese online community where users can join different types of interest groups (e.g., "Sports", "Music", "Health", "Academic") to leave comments or recommend topics to their friends. They found that all the five personality traits as defined in FFM significantly affect users' preferences for group types. For instance, groups about "Health" and "Sports" are more preferred by people who are more self-organized (with high conscientiousness) and extroverted (with high extraversion). Groups related to aesthetics (e.g., "Art" and "Literature") and entertainment (e.g., "Animation", "Music" and "Movie") are more preferred by people who are more creative and aesthetic sensitive (with high openness). Those people also prefer the groups about "Academic" and "Interest". Moreover, people who are more suspicious (with low agreeableness) tend to prefer "Movie" type group, whereas those who are more emotionally unstable (with high neuroticism) are likely to prefer "Costume" type groups.

In an experiment based on a contextual movie recommender system dataset (the CoMoDa dataset [71]), Odic et al. explored the relations between personality factors and the induced emotions in movies in different social contexts [72]. They observed different patterns in experienced emotions for users in different social contexts (i.e., alone vs. not alone) as functions of the extraversion, agreeableness and neuroticism

[2] https://www.douban.com/group/explore.

factors. People with different values of the conscientiousness and openness factors did not exhibit different patterns in their induced emotions.

A personal characteristic related to the consumption of multimedia content was identified by Tkalcic et al. [96]. Based on positive psychology research they observed that users differ in their preferences in terms of hedonic quality of the content (pure pleasure, fun) and eudaimonic quality (looking for deeper meaning): making users more or less pleasure or meaning-seekers.

3 Personality Acquisition

The acquisition of personality factors is the first major issue in the design of a personality-based recommender system. Generally, the acquisition techniques can be grouped into:

- explicit (or called direct) techniques (questionnaires depending on the model);
- implicit (or called indirect) techniques (e.g., regression/classification based on social media streams).

While explicit techniques provide accurate assessments of the user's personality, they are intrusive and time consuming. Hence, these techniques are useful mainly in laboratory studies or for performing as ground truth data to assess the accuracy of implicit acquisition method.

Implicit techniques, on the other hand, offer an unobtrusive way of acquiring user personality, by normally using machine learning techniques to infer it with features as extracted from users' digital traces. However, the accuracy of these instruments is not high and depends heavily on the quality of the source information (e.g., how often a user tweets).

In this section we survey existing techniques for the acquisition of personality in recommender systems. Table 3 summarizes the methods described in this section.

3.1 Explicit Personality Acquisition

A widely used questionnaire for assessing the FFM factors is the International Personality Item Pool (IPIP) set of questionnaires [38]. The IPIP's web page[3] contains questionnaires with 50 and 100 items, depending on the number of questions per factor (10 or 20). The relatively high number of questions makes it an accurate instrument, although it is time consuming for end users to answer. Furthermore, it has been translated in many languages and validated in terms of cross-cultural differences [61].

[3] http://ipip.ori.org/.

Table 3 Personality acquisition methods

Ref.	Method	Personality model	Source
[24, 38–41, 48]	Explicit	FFM	Questionnaires (from 10 questions up)
[74]	Implict	FFM	Micro-blogs (Twitter)
[4, 53, 83]	Implicit	FFM	Social media (Facebook)
[36]	Implicit	FFM	Social media (Weibo)
[57]	Implicit	FFM	Role-playing game
[25]	Implicit	FFM	Game (Commons Fishing Game)
[17]	Implicit	FFM	Mobile phone logs
[85]	Implicit	FFM	Emails
[45]	Implicit	FFM	Ratings of products in a webstore
[23]	Implicit	FFM	Stories
[8]	Implicit	FFM	Eye gaze
[32]	Implicit	FFM	Images, social media (Instagram)
[33]	Implicit	FFM	Privacy preferences
[35]	Implicit	FFM	Drugs consumption profile
[89]	Explicit	Thomas-Kilmann conflict model	Questionnaire
[87]	Explicit	Felder and Silverman Learning Style Model	Questionnaire

In the questionnaire defined by Hellriegel and Slocum [41], each factor is measured via 5 questions, so there are 25 questions in total regarding the five personality factors. Each factor's value is the average of user's scores on its related five questions. For example, the questions used to assess openness to experience include "imagination", "artistic interests", "liberalism", "adventurousness", and "intellect". Users are required to respond to every question on a 5-point Likert scale (for example, "imagination" is rated from 1 "no-nonsense" to 5 "a dreamer"). John and Srivastava [48] developed a more comprehensive list containing 44 items, called Big Five Inventory (BFI), in which each personality factor is measured by eight or nine questions. For example, the items related to openness to experience are "is original, comes up with new ideas", "is curious about many different things", "is ingenious, a deep thinker", "has an active imagination", etc. (each is rated on a 5-point Likert scale from "strongly disagree" to "strongly agree", under the general question of "*I see Myself as Someone Who* ..."). This questionnaire has been recognized as a well-established measurement of personality traits. The other commonly used public-free instruments include the 100-item Big Five Aspect Scales (BFAS) [24] and the 100 trait-descriptive adjectives [39]). A super-short measure of the FFM is the Ten Item Personality Inventory (TIPI) in which each factor is only assessed by two questions (e.g., openness to experiences is assessed by "open to new experiences, complex" and "conventional, uncreative" on the same Likert scale used in BFI) [40]. This instrument can meet the need for a very short

Table 4 The ten-items personality inventory questionnaire [40]

FFM factor	Statement: "*I see myself as ...*"
E	Extraverted, enthusiastic.
A	Critical, quarrelsome.
C	Dependable, self-disciplined.
N	Anxious, easily upset.
O	Open to new experiences, complex.
E	Reserved, quiet.
A	Sympathetic, warm.
C	Disorganized, careless.
N	Calm, emotionally stable.
O	Conventional, uncreative.

measure (e.g., when time is limited), although it may somewhat create diminished psychometric properties. We provide the TIPI questionnaire in Table 4.

A typical example of a commercially controlled instrument is the NEO PI-R (with a 240-items inventory) [19], which cannot only measure the five factors, but also the six facets (i.e., sub-factors) of each factor. For example, extroversion contains six facets: Gregariousness (sociable), Assertiveness (forceful), Activity (energetic), Excitement-seeking (adventurous), Positive emotions (enthusiastic), and Warmth (outgoing). The NEO-FFI instrument, which measures the five factors only (not their related facets), is a 60-item truncated version of NEO PI-R [19].

A quasi-explicit instrument for measuring personality is the approach of using stories. In their work, Dennis et al. [23] developed a set of stereotypical stories, each of which conveys a personality trait from the FFM. Specifically, for each of the five FFM factors they devised a pair of stories, one for a high level of the observed factor and one for the low level of the observed factor. The subject then rates how well each story applies to her/him on a Likert scale from 1 (extremely inaccurate) to 9 (extremely accurate).

Though different instruments have been developed so far, the choice of instrument is highly application-dependent and there is no one-size-fits-all measure. In Sect. 4, we will survey the instruments that have been adopted in recommender systems (e.g., see Table 6).

3.2 Implicit Personality Acquisition

Quercia et al. [74] presented the outcomes of a study that shows strong correlations between features extracted from users' micro-blogs and their respective FFM factors. The authors used the myPersonality dataset of 335 users. The dataset contains the users' FFM personality factors and the respective micro-blogs. The authors extracted several features from the micro-blogs and categorized them into the following quantities: listeners, popular, highly-read, and influential. Each of these quantities showed a strong correlation with at least one of the FFM factors.

The authors went a step further into predicting the FFM factors. Using a machine learning approach (the M5-Rules regression and the 10 fold-cross validation scheme), they were able to achieve a predictability in RMSE ranging from 0.69 to 0.88 (on FFM factors ranging from 1 to 5).

Kosinski et al. [53] used the whole myPersonality dataset of over 58,000 users with their respective Facebook activity records to predict the FFM factors of the users. The source dataset was the user-like matrix of Facebook Likes. The authors applied the Singular Value Decomposition (SVD) method to reduce the dimensionality of the matrix and used the Logistic Regression model to predict the FFM factors (along with other user parameters such as gender, age, etc.). Their model was able to predict the traits openness and extraversion with correlations being at least 0.40, while the other traits were predicted with lower accuracy (with correlations no more than 0.30).

An interesting approach was taken by van Lankveld et al. [57] who observed the correlation between FFM factors and the users' behaviour in a videogame. They modified the Neverwinter Nights (a third-person role-playing video game) in order to store 275 game variables for 44 participants. They used variables that recorded conversation behavior, movement behavior and miscellaneous behavior. They found significant correlations between all five personality traits and game variables in all groups.

Chittaranjan et al. [17] used mobile phone usage information for inferring FFM factors. They used call logs (e.g., outgoing calls, incoming calls, average call duration, etc.), SMS logs and application-usage logs as features for predicting the FFM factors. They observed that a number of these features have a significant correlations with the FFM factors. Using the Support Vector Machine classifier, they achieved better results in the prediction of the traits than a random baseline, although the difference was not always significant, which makes the task of inferring personality from call logs a hard one.

Shen et al. [85] attempted to infer the email writer's personality from her/his emails. To preserve privacy, they only extracted high-level aggregated features from email contents, such as bag-of-word features, meta features (e.g., TO/CC/BCC counts, importance of the email, count of words, count of attachments, month of the sent time, etc.), word statistics (e.g., through part-of speech tagging and sentiment analysis), writing styles (in greeting patterns, closing patterns, wish patterns, and smiley words), and speech act scores (for detecting the purpose of work-related emails). These groups of features were then applied to train predictors of the writer's personality, through three different generative models: joint model, sequential model, and survival model. The experiment done on over 100,000 emails showed that the survival model (with label-independence assumption) works best in terms of prediction accuracy and computation efficiency, while joint model performs worst in terms of inferring personality traits such as agreeableness, conscientiousness, and extraversion. The results to some extent infer that the personality traits are relatively distinct and independent from each other. Furthermore, it was found that people with high conscientiousness are inclined to write long emails and use more characters;

people with high agreeableness tend to use more "please" and good wishes in their emails; and people with high neuroticism use more negations.

The set of studies done by Oberlander et al. [47, 68] showed that personality can be inferred also from blog entries. In [47] they used features such as stemmed bigrams, no exclusion of stopwords (i.e., common words) or the boolean presence or absence of features noted (rather than their rate of use) to train the Support Vector Machine classifier. On a large corpus of blogs, they managed to predict the FFM factors (high-low groups for each trait) with an accuracy ranging from 70% (for neuroticism) to 84% (for openness).

With the development of social networking, some researchers have begun to study the correlation between users' personality and their social behavior on the Web (e.g., Facebook, Twitter) [4, 7, 81]. For example, [4] found strong connection between users' personality and their Facebook use through a user survey on 237 students. Participants' personality was self-reported through answering the NEO PI-R questionnaire. The collected personality data were then used to compute correlation with users' Facebook information (such as basic information, personal information, contact information and education, and work information). The results show that extroversion has a positive effect on the number of friends. Moreover, individuals with high neuroticism are more inclined to post their private information (such as photos). The factor openness was found to have positive correlation with users' willingness to use Facebook as a communication tool, and the factor conscientiousness is positively correlated with the number of friends. In [83], a similar experiment was performed. They verified again that extroversion is significantly correlated with the size of a user's social network. Moreover, people tend to choose friends who are with higher agreeableness but similar extroversion and openness.

In [37], the authors developed a method to predict users' personality from their Facebook profile. Among various features, they identified the ones that have a significant correlation with one or more of the FFM personality traits based on studying 167 subjects' public data on Facebook. These features include linguistic features (such as swear words, social processes, affective processes, perceptual processes, etc.), structural features (number of friends, egocentric network density), activities and preferences (e.g., favorite books), and personal information (relationship status, last name length in characters). Particularly, the linguistic analysis of profile text (which is the combination of status updates, About Me, and blurb text) was conducted through Linguistic Inquiry and Word Count (LIWC) program [73], which is a tool to produce statistics on 81 different text features in five psychological categories. They further proposed a regression analysis based approach to predict the personality, in two variations: M5-Rules and Gaussian Processes. The testing shows that the prediction of each personality factor can be within 11% of the actual value. Moreover, M5-Rules acts more effective than Gaussian Processes, with stronger connection to openness, conscientiousness, extroversion, and neuroticism.

Gao et al. [36] proposed a method for inferring the users' personality from their social media contents. To be specific, they obtained 1766 volunteers' personality values and Weibo behavior (which is a popular micro-blog site in China) to train the prediction model. 168 features were extracted from these users' Weibo status, and then classified into categories including status statistics features (e.g., the total number of statuses), sentence-based features (the average number of Chinese characters per sentence), word-based features (the number of emotion words), character-based features (the number of commas, colons, etc.), and LIWC features. They then applied M5-Rules, Pace Regression and Gaussian process to make prediction. The results show that the Pearson correlation between predicted personality and user self-reported personality can achieve 0.4 (i.e., fairly correlated), especially regarding the three traits conscientiousness, extroversion, and openness.

Hu and Pu studied the effect of personality on users' rating behavior in recommender systems [45]. They conducted an online survey and obtained 86 participants' valid ratings on at least 30 items among a set of 871 products (from 44 primary categories) as crawled from gifts.com. The rating behavior was analyzed from four aspects: number of rated items, percentage of positive ratings, category coverage (CatCoverage), and interest diversity (IntDiversity). The CatCoverage is measured as the number of categories of rated items. The IntDiversity reveals the distribution of users' interests in each category, formally defined as the Shannon index according to information theory. They calculated the correlation between users' FFM personality traits and the rating variables through Pearson product-moment. The results identify the significant impact of personality on the way users rate items. Particularly, conscientiousness was found negatively correlated with the number of ratings, category coverage and interest diversity, which indicates that conscientious users are more likely to prefer providing fewer ratings, lower level of category coverage, and lower interest diversity. In addition, agreeableness is positively correlated with the percentage of positive ratings, implying that agreeable people tend to give more positive ratings. All these findings show correlations between personality and rating behavior on the samples collected. However, they did not infer personality from rating behavior in this work.

Dunn et al. [25] proposed, beside an explicit questionnaire, a gamified user interface for the acquisition of personality for recommender systems. Through the Commons Fishing Game (CFG) interface the users were instructed to maximize the amount gathered from a common resource, which was shared amongst a group of players; collectively trying not to deplete this resource. The experiment showed that it is possible to predict extraversion and agreeableness with the described instrument.

More approaches have emerged in the very recent years. Machine learning predictive models have been trained on a wide variety of digital traces. For example, Instagram features, both image-based and comment-based, were used in [32, 34, 86]. A very stable and accurate prediction of personality has been demonstrated in [8], where the authors showed subjects a set of visual stimuli (a subset of pictures from the IAPS dataset [11]) and recorded their eye gaze movements. An interesting approach has been demonstrated by Ferwerda et al. [35], where they showed that personality traits can be predicted even from reports of drug consumption of users.

3.3 Datasets for Offline Recommender Systems Experiments

Given that a number of research activities has already been published, there exist some datasets that can be used for developing personality-based recommender systems. The minimal requirements for such a dataset are (a) to include the user-item interaction data (e.g., clicking or ratings) and (b) to include the personality factors associated to the users. In this subsection we survey a number of such datasets, which are summarized in Table 5.

The first dataset containing personality factors was the LDOS-PerAff-1 [98].[4] Based on 52 subjects it contains ratings of images. The user-item matrix has values for all its entries (i.e., sparsity is zero). The dataset contains the corresponding FFM factors for each user. The FFM factors were acquired using the 50-items IPIP questionnaire [38]. Furthermore, all items were selected from the IAPS dataset of images [56] and were annotated with the values of the induced emotions in the valence-arousal-dominance (VAD) space.

The LDOS-CoMoDa (Context Movies Dataset) dataset[5] [54] was released for research on context-aware recommender systems. It contains FFM data of 95 users. The FFM factors were collected using the 50-items IPIP questionnaire [38]. The dataset is also rich in contextual parameters such as time, weather, location, emotions, social state, etc.

A dataset that contains more users is the myPersonality dataset[6] [53]. It contains FFM factors of 38,330 users. The dataset was collected using a Facebook application. It contains the Facebook Likes for each of the users. Furthermore, it contains twitter names for more than 300 users, which opens new possibilities for crawling these users' micro-blogs (as has been done in [74]).

Chittaranjan et al. [17][7] presented a dataset of mobile phone users' logs along with the respective FFM values (as measured using the TIPI questionnaire). The dataset contains information of 177 subjects and their daily phone usage activities (the CDR—call data record) over a period of 17 months on a Nokia N95 smartphone. The phone usage logs contain data related to calls, SMSs and application usage.

Recently, Wang et al. [100] released a dataset[8] containing 11,383 users' feedback on recommendations that they received on a commercial e-commerce application (Mobile Taobao). In addition to obtaining users' self-reported assessments of the recommendation from various aspects (e.g., relevance, novelty, unexpectedness, serendipity, timeliness, satisfaction, and purchase intention), they acquired users'

[4] http://markotkalcic.com/resources.html.

[5] https://www.lucami.org/en/research/ldos-comoda-dataset/.

[6] https://sites.google.com/michalkosinski.com/mypersonality (the dataset was stopped sharing in 2018).

[7] The dataset is not publicly available anymore.

[8] https://www.comp.hkbu.edu.hk/~lichen/download/TaoBao_Serendipity_Dataset.html.

Table 5 Overview of datasets

Name	Ref.	Domain	Personality model	Number of subjects	Other metadata
LDOS-PerAff-1	[98]	Images	FFM	52	Item induced emotions in the VAD space
LDOS-CoMoDa	[54]	Movies	FFM	95	Movie context metadata (location, weather, social state, emotions, etc.)
myPersonality	[53]	Social Media (Facebook)	FFM	38,330	Twitter names
Chittaranjan	[17]	Mobile phone usage	FFM	117	Call logs, SMS logs, app logs
Taobao Serendipity	[100]	e-Commerce	Curiosity & FFM	11,383	User perceptions w.r.t. recommendation relevance, serendipity, satisfaction, purchase intention, etc.; click and purchase behaviors

curiosity (via Ten-item Curiosity and Exploration Inventory-II (CEI-II) [49]) and FFM personality values (via Ten-Item Personality Inventory (TIPI) [40]).

Furthermore, a number of datasets, not released as datasets per se, exist, as they have been used in the studies reported in this chapter.

4 How to Use Personality in Recommender Systems

In this section, we provide an overview of how personality has been used in recommender systems. The most common issues addressed are the cold-start problem and the recommendation diversification. Table 6 summarizes the various strategies described in this section.

Table 6 Survey of recommender systems using personality

Author	Recommender system's goal	Personality acquisition method	Approach
Tkalčič et al. [99]	Cold-start problem	IPIP 50	User-user similarity measure based on personality
Hu and Pu [44]	Cold-start problem	TIPI	User-user similarity measure based on personality
Elahi et al. [27] & Braunhofer et al. [12]	Cold-start problem	TIPI	Active learning, matrix factorization
Tiwari et al. [92]	Cold-start problem	TIPI	User-user similarity based both on personality and demographics
Fernández-Tobías et al. [31]	Cold-start problem	TIPI	Injecting personality factors into a matrix factorization algorithm
Khwaja et al. [51]	Cold-start problem	TIPI	Recommending well-being activities based on the congruence between the true personality and the projected personality
Yusef et al. [104]	Cold-start problem	TIPI	Clustering users using personality-based similarities to reduce sparsity
Wu et al. [103]	Diversity	TIPI	Personality-based diversity adjusting approach for recommendations
Tintarev et al. [90]	Diversity	NEO IPIP 20	Personality-based diversity adaptation
Cantador et al. [14]	Cross-domain recommendations	NEO IPIP 20	Similarities between personality-based user stereotypes for genres in different domains
Recio-Garcia et al. [77] & Quijano-Sanchez et al. [75]	Group recommendations	Thomas-Kilmann conflict model instrument	Combining assertiveness and cooperativeness into the aggregation function
Kompan et al. [52]	Group recommendations	Thomas-Kilmann conflict model instrument and NEO IPIP 20	Group satisfaction modeling with a personality-based graph model
Delic et al. [20] & Delic et al. [21]	Group recommendations	TIPI and Thomas-Kilmann conflict model instrument	An observational study method for understanding the dynamics of group decision-making
Roshchina et al. [80]	Recommendations in the traveling domain	TIPI	Text-based personality similarity measure for finding like-minded users

4.1 Addressing the New User Problem

The new user problem occurs when the recommender system does not have enough ratings from a user who has just started to use the system [3]. The problem is present both in content-based recommender systems and in collaborative recommender systems, although it is more difficult to solve within the latter. The system must first have some information about the user, which is usually in the form of ratings. In the case of content-based recommender systems, the lack of ratings implies that, for the observed user, the system does not know the preferences towards the item's features (e.g., the genre). In the case of collaborative filtering, especially in neighborhood methods, the lack of ratings for a new user implies that there are not enough overlapping ratings with other users, which makes it hard to calculate user similarities. So far this problem has been tackled with various techniques such as hybrid methods [3], adaptive learning techniques [28], or simply by recommending popular items [3].

Personality is suitable to address the new user problem. Given the assumption that the user's personality is available (e.g., from another domain), it can be used in collaborative filtering recommender systems.

For instance, personality has been used in a memory-based collaborative filtering recommender system for images [97, 99]. In an offline experiment, the authors acquired explicit FFM factors for each user and calculated the user-user distances (as opposed to similarities) using the weighted distance formula:

$$d(b_i, b_j) = \sqrt{\sum_{l=1}^{5} w_l (b_{il} - b_{jl})^2} \tag{1}$$

where b_i and b_j are the FFM vectors for two arbitrary users (b_{il} and b_{jl} are the individual FFM factors) and w_l are the weights. The weights were computed as the eigenvalues from the principal component analysis on the FFM values of all users. On the given dataset, this approach was statistically equivalent to using standard rating-based user similarity measures.

A similar approach was taken by Hu and Pu [44], but they used a different formula to calculate the user similarities. Concretely, they proposed to use the Pearson correlation coefficient to calculate the user similarities:

$$sim(b_i, b_j) = \frac{\sum_l (b_{il} - \overline{b_i})(b_{jl} - \overline{b_j})}{\sqrt{\sum_l (b_{il} - \overline{b_i})^2} \sqrt{\sum_l (b_{jl} - \overline{b_j})^2}} \tag{2}$$

and linearly combined it with rating-based similarity by controlling the contribution of each similarity measure with the weight α. They compared the proposed approach to a rating-based user similarity metric for collaborative filtering recommender systems. On a dataset of 113 users and 646 songs, the personality-based algorithm outperformed the rating-based in terms of mean absolute error, recall and specificity.

Similarly to the approaches proposed in [97] and [44], the authors of [92] used personality and demographics to calculate user-user similarities for recommending movies.

A standard approach to tackle the cold-start problem has been to use the active learning approach [28]. Elahi et al. [27] proposed an active learning strategy that incorporated user personality data. They acquired the personality information using the 10-items IPIP questionnaire through a mobile application. They formulated the rating prediction as a modified matrix factorization approach where the FFM factors are treated as additional users' latent factors:

$$\hat{r}_{ui} = b_i + b_u + q_i^T \cdot (p_u + \sum_l b_l) \tag{3}$$

where p_u is the latent factor of the user u, q_i is the latent factor of the item i, b_u and b_i are the user's and item's biases, and b_l are the FFM factors. The proposed rating elicitation method outperformed (in terms of Mean Absolute Error) the baseline (the log(popularity)*entropy method) and the random method.

In these examples, personality has been acquired directly with questionnaires. With this approach, the authors have just moved the burden of an initial questionnaire about user ratings to another initial questionnaire (for personality). However, their methods can also be applicable to the condition that the personality is available in advance, for example from other domains or acquired implicitly.

More recently, Fernandez-Tobias et al. [31] compared three approaches to mitigating the new user problem respectively based on (a) personality-based matrix factorization (MF), which improves the recommendation prediction model by directly incorporating user personality into MF; (b) personality-based active learning, which regards personality as the additional preference information for improving the output of recommendation process; (c) personality-based cross-domain recommendation, which exploits personality to enrich the user profile as obtained from auxiliary domains with the aim of compensating for the lack of user preference data in the target domain. They found that all the three personality-based methods achieve performance improvements in real-life datasets, among which the personality-based cross-domain recommendation performs the best.

In [51] the authors presented a recommendation approach for well-being activities, which is a novelty in the domain. According to the authors, the domain suffers from the new user problem. From the algorithmic perspective, the authors matched the user's personality with items (well-being activities) based on previous psychology research. Their assumption is that the true personality of users and the personality exhibited through behaviour are not necessarily the same. If there is an inconsistency between the two personalities, the subjective well-being is low. The true personality of users was collected using a standard questionnaire, whereas the exhibited personality was calculated from behavioural data and previous research on how certain behaviour matches certain personalities. Then they trained an SVM model for predicting the subjective well-being (acquired with a questionnaire as ground-truth) from the discrepancy between the true personalities and the exhibited personalities. In the next step, the authors simulated, for each user, a wide range of activity distributions. For each of these distributions they calculated the subjective well-being that a distribution yields for the active user. The recommended sets of activities were then ranked based on the calculated subjective well-being.

The new user problem was addressed by Yusefi et al. [104] clustering users with similar personalities together and treating all users in a cluster as a single user, hence enlarging the number of ratings per user. When a new user joins the system, s/he is added to one of the clusters that matches best her/his personality. Then a standard collaborative filtering algorithm is used to predict the item ratings. The evaluation of the approach was done on the South Tyrol Suggests dataset [27] with 2534 ratings given by 465 users on 249 items. The authors found out that the system performed best (in terms of MSE) when the number of clusters was between 3 and 7.

Although not addressing directly the new user problem, Roschina et al. [80] designed a collaborative filtering recommender system for hotels where the user similarities were calculated using the users' personalities. In their TWIN (Tell me What I Need) recommender system they used the inverse of the Euclidian distance to calculate user similarities. The novelty of their approach lies in the way they inferred the users' personalities: They trained a machine learning model that used Linguistic Inquiry and Word Count (LIWC) based features extracted from user generated comments.

4.2 Personalizing Recommendation Diversity

The impact of personality on users' preferences for recommendation diversity has been investigated first in [15, 90]. Diversity refers to recommending users a diverse set of items,[9] so as to allow them to discover unexpected items more effectively [64]. Related diversity approaches commonly adopt a fixed strategy to adjust the diversity degree within the set of recommendations [2, 46, 105], which however, does not consider that different users might possess different attitudes towards the diversity of items. That limitation motivates the authors of paper [15] to identify whether and how personality might impact users' needs for diversity in recommender systems. For this purpose, they conducted a user survey that involved 181 participants. For each user, they obtained her/his movie selections as well as personality values. Then, two levels of diversity were considered: the diversity in respect to individual attributes (such as the movie's genre, director, actor/actress, etc.); the overall diversity when all attributes are combined. The correlation analysis showed that some personality factors have a significant correlation with users' diversity preferences. For instance, more reactive, excited and nervous persons (high neuroticism) are more inclined to choose diverse directors, and suspicious/antagonistic users (low

[9] Here we mainly consider the so called "intra-list diversity" within a set of recommended items (see Chapter "Novelty and Diversity in Recommender Systems").

agreeableness) prefer diverse movie countries. As for the movie's release time, its diversity is preferred by efficient/organized users (high conscientiousness), while for the movie's actor/actress, its diversity is preferred by imaginative/creative users (high openness). At the second level (i.e., overall diversity), no matter how the weights placed on attributes vary, Conscientiousness was shown significantly negatively correlated with it, which means that less conscientious people generally prefer higher level of overall diversity.

Tintarev et al. applied a User-as-Wizard approach to study how people apply diversity to the set of recommendations [90]. Particularly, they emphasized the personality factor "openness to experience" as for its specific role in personalizing the recommendation diversity, because it describes users' imagination, aesthetic sensitivity, attentiveness to inner feelings, preference for variety, and intellectual curiosity (so they assumed that people with higher openness would be more willing to receive novel items). Their experiment was in the form of an online questionnaire with the aid of Amazon's Mechanical Turk (MT) service. 120 users' responses were analyzed. Each of them was required to provide some recommendation to a fictitious friend who is in one of the three conditions: high openness, low openness, and no personality description (baseline). The results did not prove the effect of openness on the overall diversity participants applied, but the authors observed that participants tend to recommend items with high categorical diversity (i.e., across genres) but low thematic diversity (inter-genre) to those who are more open to experience. In other words, users who are low on openness might prefer thematic diversity to categorical variation.

Motivated by the above findings, Wu et al. [103] have attempted to develop an approach to automatically adjusting the degree of recommendation diversity based on the target user's personality. They first validated the relationship between users' five personality traits and their preferences for diversity through a larger-scale user survey (involving 1706 users) on a commercial platform (i.e., Douban's Interest Group where users can join groups with various topics including entertainment, culture, technology, life, and so on). The results showed that the personality traits have significant impact on users' diversity preferences. For instance, more creative (with high openness) and/or more introverted (with low extraversion) person is more inclined to join different types of groups.

The authors have further developed a generalized, dynamic diversity adjusting approach based on user personality [103]. In particular, personality is incorporated into a greedy re-ranking process, by which the system selects the item that can best balance accuracy and personalized diversity at each step, and then produces the final recommendation list to the target user. Concretely, their method is mainly composed of two steps: (1) to predict a user's preference for un-experienced items, and (2) re-rank the items to meet the user's diversity preference. They adopted the greedy re-ranking technique [1], because it cannot only be easily incorporated into the existing recommender algorithms but also explicitly control the level of diversification. Formally, S denotes a candidate item set of size n for a user u, which is generated according to her/his predicted preferences for items. T denotes the re-ranked list that user u will finally receive, which includes N items ($N < n$, because the recommendation list T is reproduced from the larger set of candidate items). At each iteration, they add an item that maximizes the objective function $Score_{final}$ with the aim of achieving the trade-off between the user's preference for the item and her/his diversity preference for all items selected so far:

$$Score_{final}(u,i) = \beta * Score_{Pref}(u,i) + (1-\beta) * Score_{PersonalizedDiv}(u,i) \tag{4}$$

where $Score_{Pref}(u,i)$ denotes the user u's preference for item i, $Score_{PersonalizedDiv}(u,i)$ represents the personalized diversity degree, and the parameter β is used to balance the two types of preferences. More details can be found in [103]. Through experiments, they demonstrated that this approach can achieve better performance than related methods (including both non-diversity-oriented and diversity-oriented methods) in terms of both accuracy and diversity metrics.

Another contribution of the above work is that, in addition to standard diversity metrics such as α-$nDCG$ [18] and $Adaptive$ α-$nDCG$ [29], they proposed a new metric called *Diversity Fitness (DivFit)* in order to more precisely measure the personalization degree of recommendation diversity. It concretely calculates the fitness between the diversity degree $Div_{Rec}(u)$ within the top-N recommendation list and the user's actual diversity preference $Div_{Act}(u)$:

$$DivFit = \frac{1}{k}\sum_{u=1}^{k} |Div_{Act}(u) - Div_{Rec}(u)| \tag{5}$$

where k is the number of testing users, $Div_{Rec}(u)$ is calculated by means of Shannon Entropy over the types that the recommended items belong to, and $Div_{Act}(u)$ is calculated based on the user u's actual behavior records via Shannon Entropy. A smaller $DivFit$ means that the diversity of the recommendation list has a better fit to the user's actual diversity preference.

4.3 Other Applications

As we mentioned in the introduction, personality is domain-independent, i.e., when users are being recommended books or movies, we can use the same personality profile. This can be especially useful in cross-domain recommender systems (see also Chapter "Design and Evaluation of Cross-domain Recommender Systems"). In a study performed by Cantador et al. [14], personality factors were related to domain genres, and similarities between personality-based user stereotypes for genres in different domains were computed. Among the many cross-domain-genres combinations, we can find relations such that people who enjoy humor, mystery and romance books are associated with personality-based stereotypes similar to those for most of the music genres.

Personality can also be useful for group recommendations. As discussed in Chapter "Group Recommender Systems: Beyond Preference Aggregation", recommending items to groups of users is not the same as recommending items to individual users [59]. Beside having to choose among strategies that address users as individuals (e.g., least misery, most pleasure etc.—see Chapter "Group Recommender Systems: Beyond Preference Aggregation" for an extensive overview), the relationships between group members play an important role. Garcia, Sanchez et al. [75, 77] proposed to use the Thomas-Kilmann conflict model [89] to model the relationships between group members in terms of *assertiveness* and *cooperativeness*. They applied the model to three group recommendation approaches (i.e., least misery, minimize penalization and average satisfaction). They collected ground truth data through a user study with 70 students who formed groups, discussed and decided which movies they would watch together in a cinema. The proposed approach showed an increase in prediction accuracy compared to the same techniques without taking into account the conflict personality model.

Similarly, Kompan et al. [52] used the Thomas-Kilmann conflict model and the FFM to model individual users. They modeled the group satisfaction with a graph-based approach where vertices represent users and edges represent user influences based on relationship, personality and actual context. They performed a small-scale user study with users' ratings on movies. The usage of the personality-based group satisfaction model in an average-aggregation strategy-based group recommender system outperformed the same algorithm without the proposed group satisfaction modeling.

An important step in research of group recommender systems has been done by Delic et al. [20], who introduced the influence of the group members on each others' preferences. Their work was based on the aforementioned work of Quijano-Sanchez et al. [75], who used the personal trait of conformity to generate group recommendations. Delic et al. [20] measured the FFM of real users participating in a group decision making process. They found that the choice satisfaction of group members is related to their personality. Furthermore, they found that group members with low assertiveness have a bigger discrepancy between their personal preferences and the final group decision. In their next work, Delic et al. provided further arguments for modeling group dynamics using personality, in particular the Thomas-Killman conflict model, in order to measure how the contagion of preferences works within the group [21, 95]. Conformity has been additionally studied by Nguyen and Ricci [66], who showed, through a simulations study, that different recommendation strategies (in terms of whether long-term preferences should be preferred over short-term preferences) should be applied depending on the conformity level of group participants. They further conducted an experiment [67], which simulated alternative conflict resolution styles as derived from the Thomas–Kilmann conflict model. The results reveal how the conflict resolution style takes roles within groups of members who have similar tastes versus those groups whose members have diverse preferences.

5 Open Issues and Challenges

There are quite some open issues and challenges that need to be addressed regarding the usage of personality in recommender systems. In this section we survey these open issues.

5.1 Non-intrusive Acquisition of Personality Information

The limitation of traditional explicit acquisition approach is that the required user effort is usually high, especially if we want to obtain their accurate personality profile (e.g., through 100-item Big Five Aspect Scales (BFAS); see Sect. 3.1). Users might be reluctant to follow the time-consuming and tedious procedure to answer all questions, due to their cognitive effort or emotional reason. Thus, the implicit, unobtrusive approach might be more acceptable and effective to build their personality profile. The critical question is then how to accurately derive users' personality traits from the information they have provided. In Sect. 3.2, we discussed various methods, such as the ones based on users' emails or their generated contents and behavior in social networking sites (e.g., Facebook, Twitter). However, the research is still at the beginning stage, and there is large room to improve the existing algorithms' accuracy. One possible solution is to explore other types of information as to their power of reflecting users' personality. For instance, since the significant correlation between users' personality and their rating behavior was proven in [45], the findings might be constructive for some researchers to develop the rating-based personality inference algorithm. The developed method might be further extended to consider the possible impacts of other actions, such as users' browsing, clicking, and selecting behavior in recommender systems. Indeed, it will be interesting to investigate the complementary roles of various resources to fulfill their combinative effect on deriving users' personality. For instance, we may infer users' personality by combining their history data left at different platforms (e.g., the integration of rating behavior, email, and social media content). The different types of information might be heterogenous in nature, so how to effectively fuse them together might be an open issue.

5.2 Larger Datasets

The recommender systems oriented datasets containing personality factors of users are still very few (see Sect. 3.3). Furthermore the number of subjects in most datasets is low, ranging from roughly 50 to a little more than 100, with the exception of the myPersonality dataset (38,330 subjects) and the Taobao Serendipity dataset (11,383 subjects). Compared to the huge datasets that the recommender systems community is used to work with (e.g., the MovieLens 25M Dataset[10] with 25 million ratings given by 162,000 users, and the Music Streaming Sessions Dataset with 160 million listening sessions [13]), the lack of bigger datasets is an obvious issue that needs to be addressed.

5.3 Cross-Domain Applications

Personality appears to be a natural fit to cross-domain recommender systems (see also Chapter "Design and Evaluation of Cross-domain Recommender Systems"), because personality is domain-independent and can hence be used as a generic user model. Cross-domain applications have been researched in the past and correlations of preferences among different domains have been identified. For example, Winoto et al. [101] observed the relations between the *games*, *TV series* and *movie* domains, while Tiroshi et al. [91] observed the relations between *music*, *movies*, *TV series*, and *books*. The first to explore the potential role of personality in cross-domain applications was Cantador et al. [14], who observed the relations between the FFM factors and preferences in various domains (e.g., movies, TV shows, music, and books). An intuitive continuation of this work is the application of the personalities learned in one domain to another domain to mitigate the cold-start problem.

Another aspect of cross-domain recommendations is cross-application recommendations. In order to be able to transfer the personality profiles between applications, a standardized description of personality should be used. There has been an attempt, the *Personality Markup Language* (PersonalityML), to standardize the description of personality in user models across different domains [6].

5.4 Beyond Accuracy

Users are no longer satisfied with seeing items similar to what they preferred before, so showing ones that can be unexpected and surprising to them has increasingly become an important topic in the area of recommender systems [60]. The work on personalized recommendation diversity has revealed the role of personality in enhancing the personalization degree within a set of recommendation in terms of its overall diversity [103]. However, so far little attention has been paid to investigate the relationship between personality and users' perception of a single recommendation. The work lately published in [16] in particular studied the effect of curiosity, because it has been widely regarded as an important antecedent of users' desire for new knowledge or experiences in the field of psychology [9] and found

[10] https://grouplens.org/datasets/movielens/.

significantly correlated with the FFM values such as openness, conscientiousness, extraversion, and neuroticism [49]. Through the analysis of curiosity's moderating effect, the authors found that it cannot only strengthen the positive effect of novelty on serendipity, but also that of serendipity on user satisfaction with the recommendation. In other words, it implies that a more curious person will be more likely to perceive a novel recommendation as serendipitous, and be more satisfied with the serendipitous item.

The authors further validated such effect on a larger-scale dataset with over 11,000 users' feedback along with their curiosity and FFM personality values [100]. The results indicated that users with high curiosity, openness, conscientiousness, extraversion, or neuroticism are more likely to perceive the serendipity level of a recommendation higher. Moreover, there exist significant interaction effects between certain item features (e.g., item popularity, item category) and user characteristics on their perceived recommendation serendipity. For instance, users with low curiosity, openness, extraversion, or neuroticism are more sensitive to category difference between the current recommendation and those previously visited by the user.

The above findings thus suggest that personality cannot only be exploited to realize personalized diversity within a recommendation list, but also be likely helpful to achieve personalized serendipity with regard to a single item. For example, for people of different curiosity values, the "surprise" level of a recommendation might be adjusted to meet their propensity towards unexpected discovery. More work can be done in this direction to better optimize user experience with recommender systems.

5.5 Privacy Issues

Although all the research done so far on personality in recommender systems touched upon the sensitivity of the data, the issue of privacy has not been addressed properly yet. The fact that, in terms of personality, a user can be tagged as *neurotic* or otherwise with labels that suggest a negative trait making these data very sensitive. Schrammel et al. [82] explored if there were any differences in the degree of disclosure acceptance among users with different personalities, but found no significant differences.

The approaches for implicit personality acquisition, as described in Sect 3.2, raise ethical and privacy concerns that are beyond the scope of this chapter. Two major incidents happened in recent years that raised awareness of the dangers that such automatic processing of user digital traces can bring. In their work on emotional contagions the authors in [55] manipulated several hundreds of thousands of Facebook users without their consent. The second incident was the Cambridge Analytica scandal where the company used methods, similar to the ones described above, for psychological user profiling and political advertising. Therefore, we should increase users' awareness of how their data could be utilized, so they might be able to choose what information they would be willing to disclose online.

However, the study of Ferwerda et al. [33] has shown that personality can be inferred even from information about what a user is willing to disclose and what not. For example, people who score high on extraversion tend to prefer to disclose their preferences for food. People who score high on agreeableness tend not to disclose the places where they have lived. In general, people who score high on openness to experience have a tendency to disclose as little as possible, whereas highly agreeable people have little concerns about disclosing personal information.

6 Conclusion

In this chapter we presented the usage of personality in recommender systems. Personality, as defined in psychology, accounts for the most important dimensions in which individuals differ in their enduring emotional, interpersonal, experiential, attitudinal, and motivational styles. It can be acquired using either questionnaires or by inferring implicitly from other sources (e.g., social media streams). The most common model of personality is the Five Factor Model (FFM), which is composed of the five factors: openness, conscientiousness, extraversion, agreeableness, and neuroticism. This model is suitable for recommender systems since it can be quantified with feature vectors that describe the degree each factor is expressed in a user. Furthermore, the FFM (and personality in general) is domain independent. We presented several methods for the acquisition of personality factors, with a special focus on implicit methods. We showcased a number of ways recommender systems have been shown to improve using personality models, especially in terms of the cold-start problem and diversity personalization. Finally, we provided a list of open issues and challenges that need to be addressed in order to improve the adoption of personality in recommender systems.

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