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Examining the Impact of Personality on the Efficiency of Recommendation Systems

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Abstract. **Personality-aware recommendation systems are artificial intelligence (AI) driven platforms that customize recommendations based on the unique personality traits of individual users, aiming to enhance user satisfaction and engagement. The review suggests that scientifically designed online environments or applications could provide interesting possibilities for collecting and analyzing personal, social, and mass-behavioral data. Furthermore, social media users' interest in self-present aligns well with the interests of personality researchers, which suggests valuable motivational resources. A theoretical frame- work of these possibilities is provided as well as experiences regarding the small sample review method used in this study. This paper discusses personality-aware recommendation systems. With the evolution of AI nowadays, personality-aware recommen- dation systems are considered a new research field related to AI and the psychology of personality. Also, it solves the most common problems, which are cold start and sparsity of data, of the traditional recommendation systems. The results of our comprehensive search, address the core research questions related to efficiency, personality theory, and techniques.**

Keywords—Recommendation System, Personality Theories, Personality-Aware Recommendation Systems, Big five; Hybrid Recom- mendation.

I. INTRODUCTION

system model collects user ratings of items in a user preference database and subsequently uses

Technology development in recent years has led to the devel- opment of many systems and technologies used in these systems, the most prominent of which is recommendation systems. It is an intelligent machine learning algorithm that suggests items to users that interest them or are relative to them. These systems use several data and criteria to create personalized recommendations, such as search histories, recent purchases, frequently interacted items, and many other factors. Recommendation systems have been around for decades, but they have received great interest and they become important in

them to predict and recommend items that suit the user's preference [2]. It works by suggesting

recent years; due to the benefits they provide to users. Recommendation systems are used in many ap- plications in various industries such as entertainment, education, e-commerce, and many others, many systems have become depen- dent on them such as music, movies, and tourism systems. There are different techniques of recommendation systems models, such as collaborative filtering, content-based filtering, hybrid filtering, and personality-aware filtering [1]. The collaborative filtering

new items to the user based on a group of other users who share the same rating with the user; this group is called the user's neighbors, and then the system searches for items with a high rating among these neighbors and the system suggests them to the user [3]. The content-based filtering is a basic model in recommendation sys- tems and was mainly used in early recommendation systems. In this system, items are recommended based on their similarity to other items chosen by the user previously [2]. Hybrid filtering is a combination of the two models that were introduced previously. Hybrid filtering was found to solve the limitations found in those models and improve the performance of recommendation systems [3].

Moreover, group recommendation systems are designed to sug- gest items that align with the interests of a collective. These sys- tems find application in various situations, such as when a group of friends is selecting a movie to watch as a team [1]. Personality- aware meta-paths filtering is a recommendation technique that

customizes suggestions based on user personality traits and inter- ests, thereby improving the suitability of product recommendations [4]. Matrix factorization is widely used to leverage user personality extracted from their rating behavior, addressing the cold start prob- lem [5]. Model-based recommendation techniques combine user preferences, personality models, and topic features to offer per- sonalized suggestions, utilizing machine learning models trained on labeled text data [6]. Finally, Personality-based product filter- ing and interest mining provide personalized recommendations by considering the user's personality traits and interests [7]. Our fo- cus in this research will be on personality-aware recommendation systems and the theories used.
This paper aims to conduct a comprehensive exploration of previous studies and identify gaps that require further exploration. Our search strategy focused on personality theory and the rec- ommendation technology in use. We excluded older studies and prioritized the most recent ones. We organized and summarised the findings from these studies, helping us gain a comprehensive overview of the existing literature in the field. Multiple reviewers are involved in evaluating potential biases to ensure a more reliable and objective evaluation. this personality-aware review provides recommendations for future research directions, contributing to the ongoing advancement of personality-aware recommendation systems.
The objective of a personality-aware recommendation systems review is to explore theories for analyzing data, and different tech- niques and discuss the challenges that personality-aware recom- mendation systems can face. Various recommendation system techniques, including collaborative filtering, content-based filter- ing, personality-aware recommendation, and hybrid filtering, have been elucidated. Additionally, diverse personality theories such as Big Five, Eysenck, HEXACO, and MBTI have been explored. The methodology of this work is explained by identifying the research criteria centered on personality-aware recommendation systems and excluding older studies.
The research questions of this paper are:

• RQ1. Can Personality-Aware Recommendation Systems Enhance the Efficiency of Recommendation Systems?

• RQ2. How do Personality-Aware Recommendation systems utilize psychological personality theories to enhance user recommendations and experiences?

• RQ3. What are the techniques that are most accurate in personality-aware recommendation systems?

The remainder of this paper is organized as follows: In sec- tion 2, related work about personality theories is presented. In section 3, we discuss our search strategy, data analysis, inclusion and exclusion criteria, and data extraction methods. In section 4, explore the findings of the analysis and the data extracted from the studies. Section 5, examines the findings obtained from this work, identifies the gaps in studies that require further exploration, and provides recommendations for future research directions. In section 6, the conclusion of the main findings of this work.

II. RELATED WORK

This section presents personality-aware recommendation sys- tems, related personality theories, and the measurement of effi- ciency within personality-aware recommendation systems for the study.

A) Personality-Aware Recommendation

Personality-aware recommendation systems are like hy- brid filtering, as they use the same techniques, but the only difference is that they add the user’s personality informa- tion to the recommendation. It measures the personality of the user by answering a personality assessment ques- tionnaire during registration or done automatically by the system to identify the personality from previously available data. Then, the system tries to match it (the user’s person- ality type) with the relevant elements. Also, when a user has similar personality traits to other users, that’s used to identify a user’s neighbors [3].

Personality-aware recommendation systems are consid- ered among the best systems, they address the primary chal- lenge faced by recommendation systems, known as the cold start problem. This problem arises when the system has limited or no data about new users, making it difficult to provide accurate recommendations. By using the user’s per- sonality to recommend items without referring to previous data about the items, as they are more closely linked to the user himself [3].

B) Personality Theories

There are many personality theories proposed by psy- chologists over the years. It aims to provide a framework for understanding human personality, including the causes and motivations for thoughts, behaviors, and social interactions. These theories have been used in personality-aware recom- mendation systems to accurately predict what attracts the user and what he wants. The most common theories have been listed and explained:

1) Big-Five

The Big Five is one of the theories in psychology and the most widely used in personality-aware recom- mendation systems. It is also known as the Five Factor Model (FFM). It consists of five factors: Openness, Extraversion, Conscientiousness, Agreeableness, and Neuroticism, abbreviated as OCEAN [8].

Here is a brief description of the factors:

- Openness: imagination, creativity, and curiosity.
- Extraversion: sociability, assertiveness, and out- goingness.
- Conscientiousness: organization, responsibility, and reliability.
- Agreeableness: kindness, empathy, and forgive- ness.
- Neuroticism: emotional instability, anxiety, and moodiness.

2) Eysenck

Eysenck’s theory of personality is a biological the- ory based primarily on genetics and physiology and is one of the most influential theories in the field of psy- chology. Eysenck’s theory focused on temperament, which he believed was largely controlled by genetic influences and had three main factors: extraversion, neuroticism, and psychoticism [8].

3) HEXACO

The HEXACO personality theory is a sixdimensional model of human personality proposed by Ashton and Lee [8]. It is an extension of the Big Five model. The six dimensions are Honesty-Humility (H), Emotionality (E), Extraversion (X), Agreeable- ness (A), Conscientiousness (C), and Openness (O). The HEXACO model is unique because it adds the di- mension of honesty and humility ”Greed Avoidance, Sincerity, Modesty”.

4) Myers Briggs Type Indicator (MBTI)

A personality assessment tool that classifies indi- viduals into one of 16 personality types and is rarely used in personality computing. The MBTI defines per- sonality as types rather than traits (like the Big Five and HEXACO) and is defined based on four dimensions: intuition or sensing, feeling or thinking, extraversion or introversion, and perceiving or judging. Then, one letter is taken from each dimension to create a four- letter personality type such as ISTP, ISTJ, ISFP, INTP, and the list goes on [8].

5) Positive psychology

Positive psychology focuses on studying and pro- moting factors contributing to human well-being, em- phasizing happiness, fulfillment, and optimal function- ing. Optimism and pessimism are key characteristics of users that significantly influence their ratings. Users who consistently rate higher than average are typically considered more optimistic, while those consistently rated lower are viewed as more pessimistic [5].

C) Efficiency

D) Measurement To evaluate the effectiveness of personality-aware recom- mendation systems, we employ an efficiency measurement approach. This approach is crucial for understanding how well the system performs in providing accurate recommen- dations tailored to users' personalities. We use the following equation to calculate the efficiency:

$$Efficiency = \frac{Numberof\,CorrectRecommendations}{TotalNumberof\,Recommendations} \times 100$$

This equation quantifies the system's ability to make ac- curate recommendations based on users' personality traits. It measures the percentage of correct recommendations out of the total recommendations generated. A higher efficiency score indicates that the system is more adept at suggesting items that resonate with users' personalities, thereby enhanc- ing user satisfaction and engagement.

Furthermore, we discuss the dataset used and the quality of the personality theory in personality-aware recommenda- tion systems. The dataset needs to be diverse and represen- tative, while the personality theory should be well-defined and applicable to ensure accurate recommendations and user satisfaction.

III. METHODS

This section serves as a roadmap for how the work was con- ducted, outlining the key steps, criteria, and processes employed to identify, select, and analyze relevant studies. In this section, we will detail the systematic search strategy, inclusion and exclusion criteria, data extraction methods, and the synthesis process em- ployed to identify, categorize, and evaluate the available literature on personality-aware recommendation systems.

We conducted a comprehensive search using Google Scholar, ACM, and the ScienceDirect database to find relevant studies re- lated to our research on personality-aware recommendation sys- tems. We used combinations of keywords (e.g., ”personality- aware,” ”personality recommendation system,” ”personality the- ory recommendation system”). Our search strategy focused on personality theory and the recommendation technology in use. We excluded older studies and prioritized the most recent ones. The included studies have been screened by multiple reviewers. This method ensures the reliability of this work. We identified 20 relevant studies, as presented in Table 1.

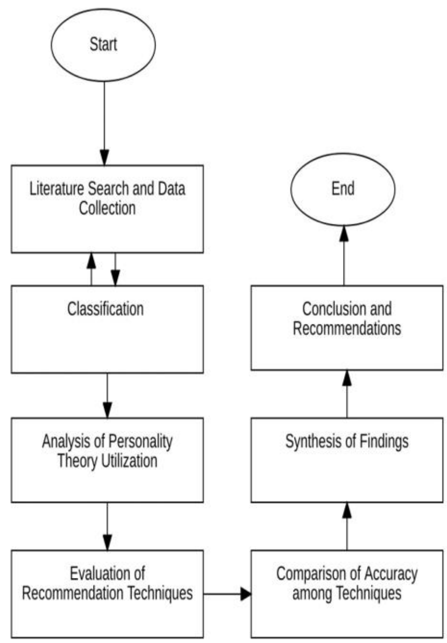

Fig. 1. Flowchart of Analysis Methodology

In this work, we carefully assessed the quality of the selected studies by using specific criteria relevant to personality-aware rec- ommendation systems. Multiple reviewers were involved in eval- uating potential biases in these studies, ensuring a more reliable and objective assessment. Figure 1 demonstrates the flowchart utilized to analyze personality-aware recommendation systems in our review. We begin with conducting a comprehensive literature search and collecting relevant data from various sources. For data synthesis, we systematically organized and summarised the find- ings from these studies, helping us gain a comprehensive overview of the existing literature in the field. We then analyze how differ- ent personality theories are utilized in these systems to enhance recommendations. Then we evaluate the effectiveness of different recommendation techniques employed in personality-aware sys- tems. We compare the accuracy of these techniques to understand their relative performance. Subsequently, we synthesize our find- ings from the analysis and comparisons conducted. Finally, we conclude our review by summarizing key insights and providing recommendations for future research directions. Our approach aimed to minimize bias and provide a clear, well-documented synthesis of the available information, ultimately enhancing the credibility and value of this work in the field of personality-aware recommendation systems.

Table I. Personality Aware Recommendation System Comparison

Paper title	*Year*	*Personality theory*	*Recommendation technique*	*Dataset used*	*Recommended Content*
(Dhelim et al., 2023)[8]	2022	Big-Five Eysenck HEXAC O MBTI	Hybrid recommendation	Newsfullness news dataset 1229 users/ viewed 33450 articles	Generic
(Abolghasemi et al., 2022)[1]	2022	Big-five	Group recommendation	MovieLens 100 K datasets 1,128 users/ 73,078 movie ratings	Social recommendation
(Dhelim et al., 2020)[4]	2020	Big-five	Personality-aware meta-paths filtering	Newsfullness datasets 2228 users/ 25873 articles/ 6230 items	Products recommendation
(Asabere& Acakpovi,2020) [9]	2022	Big-Five	Group recommendation	ATU datasets 4396TV viewers/ 22,541 personality ratings	TV programs recommendation
(Dhelim et al., 2020) [10]	2020	Big-five	Collaborative filtering	Newsfullness datasets 1580 users/ 25873 articles	Web content recommendation
(Arijanto et al., 2021) [11]	2021	Big-five	Hybrid recommendation	Twitter datasets 791 users/ used records with more than 17 sampled tweets	Predict user personality
(Lavanya et al., 2022) [12]	2022	Undefined	Hybrid recommendation	No dataset	Product Recommendation
(Asabere, 2022) [13]	2022	Big-five	Collaborative filtering	ATU dataset 4396 users/ 22,541 personality ratings	Programme recommendations
(Nidamanuri et al., 2022)[7]	2022	Big-Five	Personality-based product filtering and interest mining.	No dataset	product recommendation
(Szmydt, 2021) [14]	2021	Big-five	Collaborative filtering	Amazon dataset 2,968,635 users /34,467,155 reviews.	Product recommendation
(Alves et al., 2023) [15]	2023	Big-five	Group recommendation	their own datasets 1035 responses	Tourist recommendation
(Klec´ et al., 2023) [16]	2023	Big-five	Hybrid recommendation	small dataset 279 users/ 5278 ratings	music recommendation
(Guo et al., 2023) [17]	2023	Undefined	Hybrid recommendation	Two datasets Lastfm and Ciao 1892 users and 7375	Social Recommendatio n

(Niranjan et al., 2022) [18]	2022	Big-five	Hybrid recommendation	No dataset	Product recommendation
(Ghezelji et al., 2022)[5]	2022	Positive Psychology	matrix factorization	MovieLens 100k datasets 943 users/ 100,000 ratings/ on 1682 movies	Movie recommendation
(Yang et al., 2022) [19]	2022	MBTI	Hybrid recommendation	their own dataset (Twitter) 41901 users	Social Recommendation
(Christodoulou et al., 2022a) [20]	2022	Big-five MBTI	collaborative filtering	TripAdvisor datasets 1535 users/437 venues.	Restaurant recommendation
(Ogunbiyi et al., 2022) [21]	2022	Big-five	content-based recommendation	review 20 tourist sites maximum review 1000	Tourist Recommendation
(Rozhevskii et al., 2022) [22]	2022	Big-five	Hybrid recommendation	Spotify datasets 34,000 artists/ 170,000 songs	Music Recommendation
(Christodoulou et al., 2022b)[6]	2022	MBTI	model-based recommendation	Cyprus datasets 93 users/ 410 venues.	Restaurant recommendation

IV. RESULT

In the results section, we explore the findings of our comprehensive exploration into a personality-aware recommendation system, addressing the core research questions related to efficiency, personality theory, and techniques.

We identified 20 potentially relevant studies through our search, con- sidering the latest research, to ensure the recentness of the research. These studies are distributed across different years, with 2 studies in 2020, 2 stud- ies in 2021, 13 studies in 2022, and 3 studies in 2023. The search strategy focused on personality theory and the recommendation technology in use. Most of the studies applied the Big Five personality theory, as shown in Figure 2. Figure 3 shows the different types of recommendation techniques used by the studies

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Fig. 2. Personality theories classification

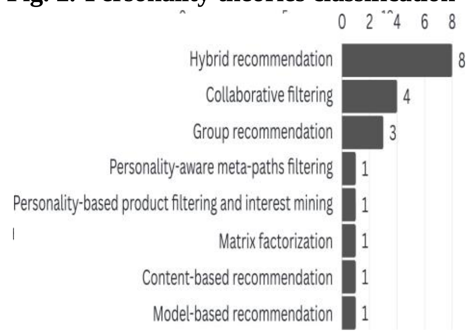

Fig. 3. Recommendation techniques classification

- **Research Question 1 (RQ1): Can Personality-Aware Recom- mendation Systems Enhance the Efficiency of Recommenda- tion Systems?**

Personality-aware recommendation systems improve the effi- ciency of recommendation systems by effectively addressing chal- lenges such as cold start problems for new users. This is achieved by leveraging the personality type model to mitigate the cold start problem [8]. Utilizing users' personality characteristics enables the system to provide initial recommendations. Moreover, prior- itizing the recommendation of items based on users' personality significantly contributes to enhancing user satisfaction.

- **Research Question 2 (RQ2): How do Personality-Aware Rec- ommendation Systems utilize psychological personality theo- ries to enhance user recommendations and experiences?**

This question leads our exploration into the theoretical foun- dations that drive personality-aware recommendation systems. For instance, research by [8] demonstrates how these systems leverage theories like the Big Five and MBTI to customize recommendations based on individual personality traits. Through an examination of how psychological personality theories are translated into action- able insights, these systems enhance both user recommendations and the overall user experience.

- **Research Question 3 (RQ3): What are the techniques that are most accurate in Personality-Aware Recommendation Sys- tems?**

Determining the most accurate techniques for a specific con- text involves examining various methods. Utilizing hybrid models that combine collaborative filtering, content-based filtering, and machine learning, along with employing deep learning and ad- vanced neural networks, contributes to enhancing accuracy. Hy- brid personality filtering is effective in leveraging the benefits of personality-matching methods [3]. Additionally, considering fac- tors like data quality and user satisfaction, analyzing users' past behaviors, adapting recommendations based on the situation, and integrating user feedback are additional techniques that enhance

accuracy.

V. DISCUSSION

advanced techniques to enhance the efficiency and accuracy of these sys- tems. We found that most research used hybrid recommendation technol- ogy and the Big Five theory mentioned in section 2 because it improves the performance and efficiency of recommendation systems and user ex- perience. Also, the use of hybrid techniques in addition to Deep Machine

In the Discussion section, we thoroughly examine the findings ob- tained from this work on personality-aware recommendation systems, aiming to identify gaps in studies that require further exploration. This discussion includes consideration of limitations and potential biases in the review process. Finally, we provide recommendations for future research directions, contributing to the ongoing advancement of personality-aware recommendation systems.

The integration of human hobbies analysis and semantic route de- velopment into a personality-aware item recommendation system was introduced by [7] with no datasets specified. On the other hand, [18] delved into product recommendation mining based on user interests and rating prediction from textual reviews, utilizing questionnaires without conducting experiments or providing clear information on datasets used.

[12] contributed to a personality-aware product recommendation sys- tem without specifying datasets and leaving the personality theory unde- fined. In the study by [17] personality traits were leveraged for enhanced graph convolutional networks-based social recommendation systems, us- ing a personality classifier, but without determining a clear definition of the personality theory being used.

The investigation by [6] involved combining user and venue personal- ity with topic modeling in restaurant recommendation systems, utilizing a small dataset with 93 users. On the other hand, [16] explored personality traits beyond the Big Five for music recommendation systems, utilizing small datasets with 279 users.

In conclusion, our examination of personality-aware recommendation systems shows a landscape of approaches, determining notable gaps such as the lack of datasets and clear definitions of personality theories. For future research, we recommend researchers use clearer definitions of per- sonality theories to enhance user recommendations and the overall user experience. researchers could explore the complex interactions between var- ious personality traits and their impact on user preferences and decision-making. Additionally, investigating the ethical implications of personality-aware recommendation systems, such as privacy concerns and potential algorithmic biases, is crucial for ensuring the responsible and ethical deployment of these systems in practice. Furthermore, there is a need for studies focusing on the development and validation of stan- dardized datasets specifically designed for evaluating personality-aware recommendation algorithms. These datasets should cover a wide range of user-profiles and preferences to ensure the generalizability of research findings.

Overall, there is an increasing need for computer scientists, psychol- ogists, and ethicists to collaborate to understand the complex dynamics involved in personality-aware recommendation systems. Advancing the techniques and theoretical foundations of these systems will enhance their robustness and practical applicability.

VI. CONCLUSION

In this paper, we provided a comprehensive exploration of previ- ous studies in the field of personality-aware recommendation systems. Through the identification of key research questions, we aimed to high- light the need for clearer definitions of personality theories and explore

Learning increases the accuracy of personality-aware recommendation systems. Personality-aware recommendation systems are currently at the fore compared to traditional recommendation techniques because they have contributed to solving the cold start problem.

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دراسة تأثير الشخصية على كلمات أنظمة التوصيات

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مستخلص. أنظمة التوصية الواعية للشخصية هي منصات تعتمد على الذكاء الاصطناعي وتخصص التوصيات بناءً على السمات الشخصية الفريدة للمستخدمين الفريدين، بهدف تعزيز رضا المستخدم ومشاركته. تشير المراجعة ان البيئات أو التطبيقات عبر الإنترنت المصممة علمياً يمكن أن توفر إمكانيات مثيرة للاهتمام لجمع وتحليل البيانات الشخصية والاجتماعية والسلوكية الجماعية. علاوة على ذلك، فإن اهتمام مستخدمي وسائل التواصل الاجتماعي بالتمثيل الذاتي يتماشى جيداً مع اهتمامات الباحثين في مجال الشخصية، مما يشير إلى وجود موارد تحفيزية قيمة. يتم توفير إطار نظري لهذه الإمكانيات بالإضافة إلى تجارب تتعلق بطريقة استعراض العينة الصغيرة المستخدمة وفي هذه الدراسة. تناقش هذه الورقة أنظمة التوصية الواعية للشخصية. مع تطور الذكاء الاصطناعي في الوقت الحالي، تعتبر أنظمة التوصية المدركة للشخصية مجال بحث جديد متعلق بالذكاء الاصطناعي وعلم الشخصية. إن هذه الانظمة تحل المشاكل الأكثر شيوعاً وهي البداية الباردة وتناثر البيانات، لأنظمة التوصية التقليدية. تعالج نتائج بحثنا الشامل الأسئلة البحثية الأساسية المتعلقة بالكفاءة ونظرية الشخصية والتقنيات. تعالج نتائج بحثنا الشامل الأسئلة البحثية الأساسية المتعلقة بالكفاءة ونظرية الشخصية والتقنيات.

الكلمات المفتاحية. نظام التوصية، نظريات الشخصية، أنظمة التوصية الواعية للشخصية، بيج فايف، التوصية الهجينة.