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Exploring the Use of Facial Attributes in Personality-Driven Recommendation Systems (FABaRS): A Survey

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Abstract: *Modern computing systems are designed to provide a personalised experience for the user. They use a variety of techniques, such as machine learning and data analytics, to tailor their interactions and results to the user's needs and preferences. This paper aims to provide an updated survey of the state of facial attribute-based personality-aware computing used specifically in recommender systems, with a focus on recent developments. The objective of this study is to outline the current themes and directions of research in the field of facial attribute-based personality-aware computing for recommenders and to provide insights into potential future developments in this area.*

Keywords: Personality-aware systems, recommendation systems, facial attributes, social computing, big five, five-factor model.

I. INTRODUCTION

Personality-aware computing is a research area that focuses on the development of computer systems that can understand, model, and adapt to individual users' personalities. The goal is to create systems that can interact with users in a more natural and personalised way, by taking into account the unique characteristics of each user's personality. The process of personality-aware computing typically involves two main steps: personality modelling and personality-aware adaptation.

In personality modelling, the system attempts to infer the user's personality based on their behaviour, interactions, or other available data. This can be done using techniques from natural language processing, computer vision, or other fields.

In personality-aware adaptation, the system uses the inferred personality information to adapt its behaviour, interactions, or other features to better suit the user's personality. For example, a personality-aware system might use a more formal or informal language style depending on the user's personality or present different types of content or recommendations based on the user's interests and preferences.

Facial characteristics are considered to be an important aspect of nonverbal communication in psychology. Researchers have found that the way a person's face is perceived can convey information about their emotions, personality, and other psychological traits. For example, a study by (Ekman, Freisen, and Ancoli 1980)[1] found that certain facial expressions, such as a smile, are universally recognized as indicating happiness.

Similarly, other studies have found that facial symmetry is associated with the perception of beauty and trustworthiness. Additionally, facial characteristics such as wrinkles, and facial expressions are also used in emotional recognition and analysis. However, it is important to note that interpreting facial characteristics is not always straightforward and is often subject to cultural and individual differences.

A strong case can be made for relying on facial characteristics in understanding personality can be seen in (Kachur, Osin, and Davydov 2020)[2]. Here, we see a consistent score in individuals guessing personality traits by viewing static face images.

Furthermore, the authors in (Kachur, Osin, and Davydov 2020)[2] also demonstrate trait prediction using Artificial Neural Networks (ANNs) to test the ability of computers to possess a similar ability as humans. As shown, a simple ANN does a decent job of doing so.

Therefore, given sufficient grounds for furthering this research, this paper will explore the current state of the work done in this domain of research, while also providing suggestions and ideas for future directions. It is also important to note, that this method of designing recommendations falls under the broader category of Visually-aware recommender systems. These recommender systems that incorporate visual information utilise visual cues present in the data to construct models of the visual attributes of items and the preferences of users towards them.

This paper aims first to provide some background into the field including terms from psychological literature and from recommendation system research. As the field does not have as much activity as other methods of recommendation systems, it also aims at showcasing the various methods used in domains adjacent to it, but are foundational.

The base assumption this paper makes about how facial attributes or characteristics-based personality-driven recommender systems can be seen in the following flow diagram.

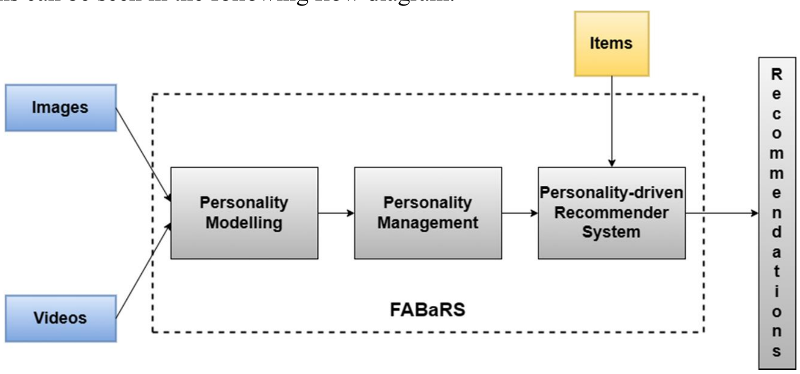

Fig. 1. General flow and architecture of FABaRS

Further in this paper, we go on to explain research in each of the sections in greater detail.

II. BACKGROUND

As this paper proceeds to review the literature in this domain, it becomes necessary to first touch upon what aspects of the face may seem useful from the vast collection of psychological literature and outline the definitions of traditional recommender systems. It can also be noted that people with similar personalities tend to like similar things (Mehta, Majumder, and Gelbukh 2020)[8]. The theory of discrete emotions (Hudlicka, 2017) [3] posits that there exist six or more elemental emotions (e.g. happiness, sadness, anger, fear, disgust, and surprise) that are universally exhibited and comprehended. This theory finds support in the evidence of cross-cultural commonalities in facial expressions and the occurrence of comparable emotions in other primates. Moreover, research conducted across several nations has demonstrated that individuals express and perceive these foundational emotions in a uniform manner.

There are several different types of traditional recommender systems, each with its own strengths and weaknesses. Some of the most common types include (Dhelim, Aung, and Bouras 2022)[4]

- *Content-Based Recommender Systems*: These systems recommend items to users based on their past preferences and behaviour. For example, a content-based recommender system for movies may recommend a movie to a user based on their past viewing history.
- *Collaborative Filtering Recommender Systems:* These systems recommend items to users based on the preferences and behaviour of similar users. For example, a collaborative filtering system may recommend a movie to a user based on the fact that other users who have similar tastes have liked that movie. There are two main types of collaborative filtering: user-based and item-based.
- *Hybrid Recommender Systems*: These systems combine the strengths of both content-based and collaborative filtering systems. For example, a hybrid system may use content-based filtering to recommend movies to a user based on their past viewing history, but then use collaborative filtering to further refine the recommendations based on the preferences of similar users.

There exists more over and above the traditional types mentioned above, but this paper only serves to introduce concepts relevant and present within the body of research it is concerned with.

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It's important to note that no single type of recommender system is best suited for all use cases, and the choice of system will depend on the specific requirements of the application and the available data.

III. MODELLING PERSONALITY IN RECOMMENDER SYSTEMS

Assessing a user's personality is crucial for a personality-aware recommendation system as any inaccuracies in the measurement can negatively impact the system's recommendations. The field of Personality Computing utilises two distinct methodologies for quantifying an individual's personality: self-reported personality assessment questionnaires and computational methods such as Automatic Personality Recognition (APR).

Generally, questionnaire-based measurement is more accurate but APR methods are easier to conduct as they can be applied to existing user data without requiring the user to complete a lengthy questionnaire. APRs can also be adapted through time, to build a multimodal system based on the user's interactions.

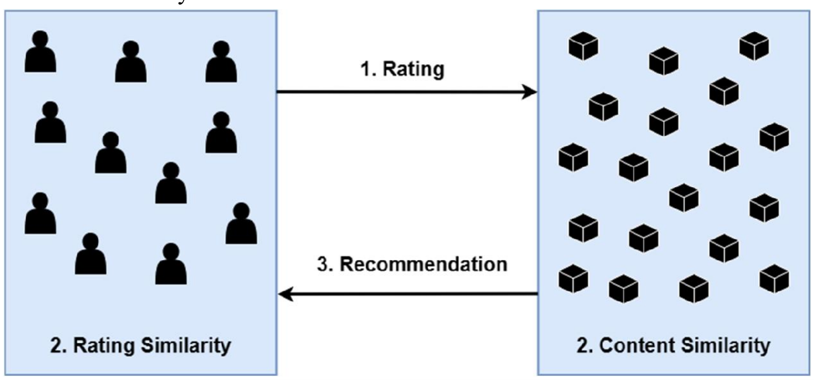

Fig. 2. Conventional recommendation systems (Dhelim, Aung, and Bouras 2022)[4]

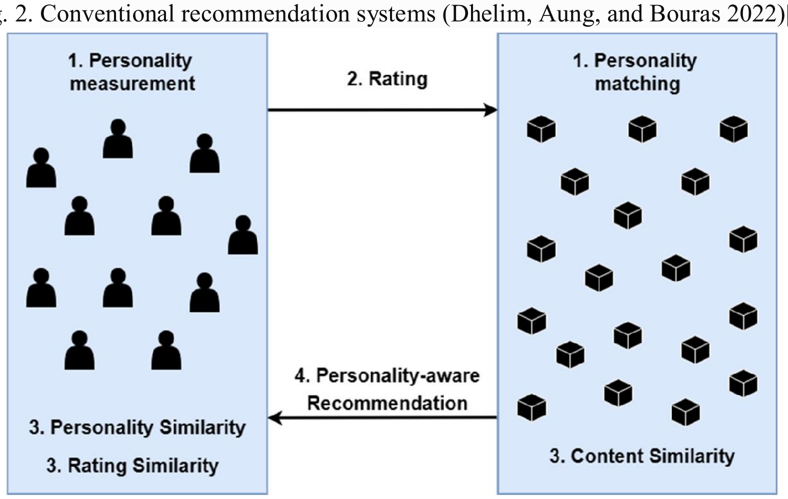

Fig. 3. Personality-aware recommendation systems (Dhelim, Aung, and Bouras 2022)[4]

The diagrams above clearly compare the different recommender systems, namely the traditional and the personality-aware ones.

(Dhelim, Aung, and Bouras 2022)[4] The conventional recommendation process is composed of three stages, namely: rating, filtering, and recommendation. In the rating stage, the users indicate their preference by rating the items. Then, the filtering stage uses techniques such as collaborative filtering, content filtering, or hybrid filtering to select a subset of items. Lastly, in the recommendation stage, the system suggests the items selected by the filtering stage to the user.

Personality-aware recommendation systems introduce additional steps before the rating phase, and also modify the filtering phase. The system starts by assessing the personality type of users through a personality assessment questionnaire or by analysing their previously available data such as online social network data. This step is known as the personality measurement phase. The subsequent stage involves the Personality Matching process, where the system determines the compatibility between the user's personality profile and relevant items. This is achieved through a calculation of the likelihood of a match between the user and the item, based on the user's personality traits and selected personality characteristics of the items. This step can be done using lexical matching or fine-grained rules. It is important to note that the system doesn't use the user's rating information at this stage which can help in overcoming the cold-start problem which is a significant challenge in recommendation systems.

IV. MEASURING PERSONALITY

The need for measuring personality has been a long-dated issue and elaborate discussions have been conducted in (Arapakis et al. 2009)[6], however as seen, the need for a standard method is essential.

The recent survey paper dated back to 2022 (Dhelim, Aung, and Bouras 2022)[4] also mentioned many other scales explored in recommender system design, such as HEXACO and MBTI.

There have been various models proposed to quantify and represent human personality. Among these, the Five Factor (FF) model, also known as the Big Five Personality Traits theory, is considered one of the most comprehensive and widely used in literature.

The FF model postulates five broad dimensions of personality: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. These dimensions are believed to capture the majority of the variance in personality traits. Openness to experience (OPE) reflects an individual's inclination towards intellectual curiosity, creativity, and preference for novel and varied experiences. Conscientiousness (COS) reflects an individual's tendency towards self-discipline, the pursuit of personal achievements, and organisation in behaviour. Extraversion (EXT) reflects an individual's inclination towards seeking stimulation in the company of others and the desire for positive emotions.

Agreeableness (AGR) reflects an individual's tendency towards kindness, cooperation, and empathy towards others. Finally, neuroticism (NEU) reflects an individual's tendency towards experiencing negative emotions and impulsivity.

V. EXTRACTING PERSONALITY FROM FACIAL ATTRIBUTES

The other approach seen in extracting personality traits from facial features is by priming the algorithm for emotion detection (Dalvi et al. 2021)[7], as personality traits and emotions are correlated and are indicative of some underlying trait (Hudlicka 2017)[3].

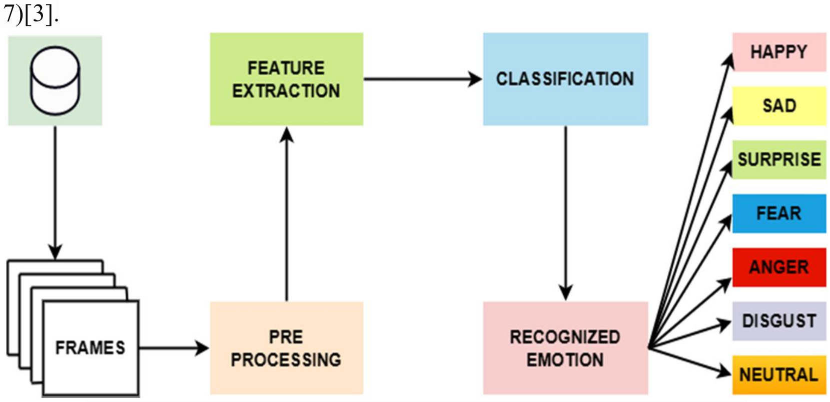

Fig. 4. Facial emotion classification process (Dalvi et al. 2021)[7]

From (Mehta, Majumder, and Gelbukh 2020)[8] we see that many models both involving deep learning and non-deep learning models are put forth. However, the performance of those with deep learning is much better and can generalise with more accuracy over unseen data; even though training such models is computationally expensive.

(Mehta, Majumder, and Gelbukh 2020)[8] Mentions Physiognomy and the use of Convolutional Neural Networks (CNNs) to classify a personality model. The following can be seen from the diagram below.

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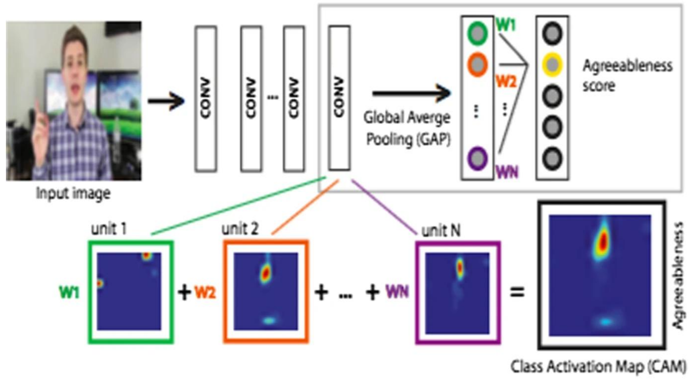

Fig. 5. Class activation map used by Ventura et al. (2017) for interpreting CNN models.

However, to further enhance trait extraction, we see in (Gucluturk et al. 2017)[9] that certain parts of an image contribute more to determining which personality trait is predicted, this process is known as Segment-level occlusion analysis. The paper also further provides an online trait recognition system. This can be visualised from the original diagram as follows:

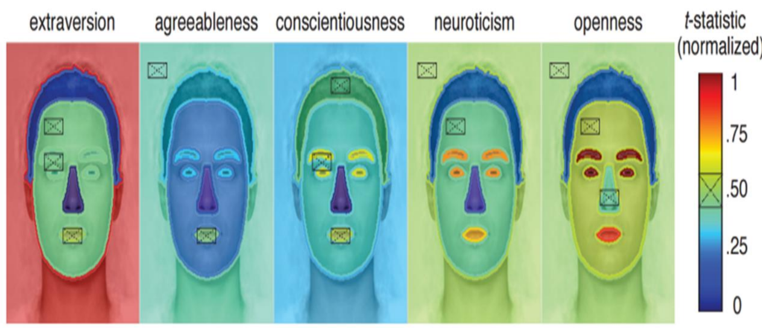

Fig. 6. Segment-level occlusion analysis visualisation (Gucluturk et al. 2017)[9]

A popular library used in extracting facial features is OpenFace capable of facial action unit recognition, and other behavioural analysis (Baltrusaitis)[10].

V. RELATED WORK

This section explores some of the work done to directly address the use of facial attributes in recommender systems.

(Chauhan, Mangrola, and Viji 2021)[11] This survey paper illustrates the various recommender systems that have been developed using facial features first to extract emotions, and later to use those to suggest movies. It also showcases research that uses facial expressions as input to recommender systems.

This paper (Chauhan, Mangrola, and Viji 2021)[11] goes on to affirm that based on its survey, for any model that relies on extracting any patterns from images CNNs provide the best performance.

(Liu et al. 2019)[12] The proposed methodology employs the Vggface face recognition network, specifically utilising the VGG-Very-Deep-16 network architecture. This architecture comprises a sequence of five convolutional layers, interleaved with pooling layers, followed by two fully connected layers and a final softmax layer for classification. The output of the first fully connected layer (FC6) is extracted as the facial feature representation, which is then utilised for downstream recognition classification tasks.

The proposed hairstyle recommendation system (Liu et al. 2019)[12] employs a feature-based approach, wherein the facial feature points of the user input image are extracted and compared with the feature points of the images stored in the database. The Euclidean distance between the feature points is computed, and the database image with the minimum distance to the user input image is identified as the most similar image. The hairstyle of the identified image is then recommended as the most suitable hairstyle for the user. This approach leverages the robustness of the Euclidean distance metric in capturing the resemblance between the facial feature points and the efficacy of the feature-based approach in capturing the distinctiveness of hairstyles.

This paper (Mariappan, Suk, and Prabhakaran 2012)[16] introduces ProASM used in Facefetch, the recommender system, a novel model for feature extraction that deviates from the deep learning-based models that have been previously proposed. ProASM is a variant of the previously proposed model, ASM (Mariappan, Suk, and Prabhakaran 2012)[16], and is based on traditional machine learning techniques. The performance of the ProASM model is noteworthy and merits attention. The model extracts relevant features from the input data and creates a content profile. This approach presents a new solution to the cold-start problem, a common issue in recommender systems, through using classical machine learning techniques such as Support Vector Machines (SVM).

(Mariappan, Suk, and Prabhakaran 2012)[16] The profile model is constructed using a four-step process that aims to extract relevant features from the input data. The process is as follows:

- Convolution: The first step is to convolve the input data with a set of filters.
- Normalisation: The second step is to normalise the output of the convolution operation. This step is important to ensure that the output of the convolution operation can be used as input for the next step.

Equalization is a technique used to adjust the contrast of the input data. It is often used in image processing to improve the visibility of an image. In this step, the normalised output is passed through an equalisation function, which adjusts the contrast of the output so that it is more suitable for the next step.

- Weight Masking: Weight masking is a technique used to assign different weights to different parts of the output. In this step, the equalized output is multiplied by a weight mask, which assigns different weights to different parts of the output. This step is important to ensure that the most relevant features are retained and the less relevant features are discarded.

Overall, the four-step process of convolution, normalisation, equalisation, and weight masking is used to extract relevant features from the input data and create a content profile. This profile is then used to make recommendations in a recommender system.

(Pauly and Sankar 2015)[27] In this research, the authors employ a computer vision technique based on Haar-like features for the purpose of facial recognition. This is accomplished by applying a set of predefined templates to extract rectangular segments from the image, followed by processing these segments through a boosting algorithm. The distinctive features of the face are represented mathematically as an eigen matrix. The authors then integrate the use of collaborative filtering, leveraging an existing dataset that has been divided into items and ratings based on gender identification. The model ultimately utilises correlations between gender, emotion, and facial features to recommend items from the dataset in a predetermined sequence.

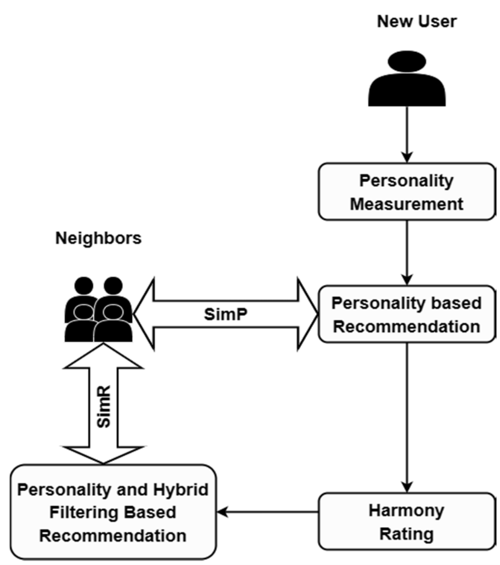

Fig. 7. PersoNet's System Design (Ning, Dhelim, and Aung 2019)[28]

Recommending people is important because it helps individuals and organisations connect with others who share similar interests, goals, and values. In social media and online communities, recommendations can help users discover new friends and build meaningful relationships. For this reason, (Ning, Dhelim, and Aung 2019)[28] present a novel recommender system that suggests users on a platform connect based on a model known as PersoNet.

The computation of recommendations is based on several considerations in this model, including, the similarity of personality traits between the user and their neighbours, compatibility of personality traits between potential friends and those users who have previously been rated (content filtration) and congruence of ratings between the user and their neighbours (CF).

The diagram below depicts the process outlined in (Ning, Dhelim, and Aung 2019)[28], which involves utilising two metrics, SimP (personality rating) and SimR (harmony rating), to model the personality of a user and assess its compatibility with other similar groups.

VI. CONCLUSION

The field of recommender systems has seen significant advancements in recent years, however, the application of visual cues and facial characteristics in the development of recommender systems is an area that remains under-explored. There exists a limited number of studies and applications that have attempted to incorporate visual information in recommender systems. This presents a significant opportunity for further research in this area.

To fully leverage the potential of visual cues in recommender systems, it is necessary to develop a system or framework that can accurately and effectively characterise facial attributes, expressions, and emotions alongside more information about the user's content profile. This includes identifying and extracting relevant features from facial images and then mapping these features to relevant personality models. Once this is achieved, the results can be seamlessly integrated into a fine-tuned multi-modal recommender system that can provide personalised recommendations based on the user's visual cues and facial characteristics.

In conclusion, the field of recommender systems has much to gain by incorporating visual cues and facial characteristics, but more research is needed to fully establish the nuanced connections between these factors and user preferences.

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