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RESEARCH PAPER

A novel subject-independent deep learning approach for user behavior prediction in electronic markets based on electroencephalographic data

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Abstract
Based on the work by Buettner (2017) showing a personality-based recommender system for electronic markets using social media data, we extend the work by proposing a novel deep learning-based engine to predict the user's personality just based on electroencephalographic brain data. As brain-computer interfaces and hybrid intelligence devices enable access to human brains, using electroencephalographic brain data becomes more relevant in future. Contrary to the majority view of previous research, our results show that there is a link between personality traits and brain features of a user. With a four times higher probability of correctly predicting the personality of an independent user compared to naive prediction, we demonstrate the possibility of predicting a user's personality based on their brain information and thus showing a new reliable approach for marketing purposes in electronic markets.

Keywords Convolutional neural network · Predictive analysis · Five-factor model · Machine learning · Personality mining · Resting-state electroencephalogram

JEL Classification C89 · C90 · D40 · M31 · M37

Introduction

Buettner (2017) has shown that personality traits (PTs) of users within electronic markets are of great interest to effectively recommend products based on their preferences. This assumes that PTs can influence user preferences and behavior (Barrick & Mount, 1991; Judge et al., 1999). The paradigm most widely used in research on PTs are the big five PTs: conscientiousness, extroversion, emotional stability, openness to experience, and agreeableness (Costa & McCrae, 1992; Goldberg, 1990). Since PTs are mainly measured via self-reported questionnaires, which are quite subjective (Boyle et al., 2008; Gosling et al., 2003) and prone to forgery (Viswesvaran & Ones, 1999), various studies have successfully attempted to identify the traits via personality mining in social networks (Buettner, 2017; Golbeck et al., 2011; Wald et al., 2012; Youyou et al., 2015). Through this technique, a more automated and accessible method for personality assessment was created. However, social media still has the problem that users can manipulate and thus falsify their digital footprint, which has an impact on the prediction of PTs (Eftekhar et al., 2014). Also, users often change their behavior in social networks (Guleva et al., 2022), impacting the classification results over time. However, PTs are actually related to an individual's biological factors, like its brain structure, and therefore represent a temporally independent characteristic that remains quite unchanged throughout a subject's lifetime (Costa & McCrae, 1992; Romero et al., 2009).

For a long time, it was science fiction to read data from our brains and make this information usable for end consumers, but several studies from the past year in particular show the potential of brain-computer interfaces (BCIs) to decode the human brain (e.g., Drew, 2023). Recent developments in consumer wearables that can read electroencephalography (EEG) data suggest that applications will have easy and constant access to our brains in the future

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(Crum, 2019). For example, earbuds, which use EEG sensors to read the user's brainwaves, have proven to be successful (Ackerman & Strickland, 2022; Chatterjee et al., 2022), resulting in Apple receiving a patent to use EEG sensors in their earbuds (Drew, 2023).

Users can hardly manipulate their brainwaves and the resulting EEG data, which makes them a suitable source for unbiased personality prediction (Brocke et al., 2013). Even though audio, video, and text are the most commonly used modalities for personality prediction (Agastya et al., 2019), current developments in machine learning (ML) and especially deep learning make it possible to use EEG data as a basis for prediction. Some studies have performed affective EEG-based prediction of the big five PTs using ML methods and were able to show correlations between the traits and the physiological data (Bhardwaj et al., 2021, 2022; Li et al., 2020a; Miranda-Correa & Patras, 2018). While this research has made great impact in showing the associations between personality and affective EEG data, the approaches are not suitable for applications in electronic markets. For these applications, a resting-state EEG solution is needed that works without external stimuli, so that data can be retrieved passively and automatically without having to assign it to an event such as a video or text. Although the current consensus in research is that no predictions about personality based on this data are possible (Korjus et al., 2015), there are initial individual studies suggesting that a correlation exists (Baumgartl et al., 2020; Jawinski et al., 2021).

Contrary to the majority view that the resting-state EEG data does not contain any information about the PTs of a subject, we hypothesize in this work: A person's personality is linked to their resting-state EEG data. The hypothesis is based on the finding that traits are related to biological factors (Romero et al., 2009). There is a need for an objective and reliable artifact for EEG-based personality assessment beyond the limitations of classical tests, realized by intelligent automation. Following this need, we state the following research question: How to design a resting-state EEG-based personality prediction engine to augment personality-based product recommendations in electronic markets?

In this work, we propose a personality prediction engine that ties in with Buettner's (2017) work and is intended to replace the social media data used in his engine. In doing so, we create a more reliable and tamper-proof alternative for electronic markets. By developing a novel convolutional neural network (CNN) architecture that uses finer-graded EEG sub-bands, to the best of our knowledge, we are the first to predict all big five PTs based on resting-state EEG data. With the successful prediction of the PTs, we can confirm the hypothesis for the present dataset. The most important contributions of our work are:

1. Successful prediction of all big five PTs from resting-state EEG data, demonstrating a reliable and passive way to predict personality based on physiological signals.
2. Presentation of an innovative Gaussian preprocessing filter for the improved subject-independent prediction of a subject's PTs.

This work is organized as follows: In the research background, we describe PTs and how they affect (electronic) markets, we present the product recommendation system of Buettner (2017) and show the required paradigms for EEG data and examine further studies in the field of EEG-based personality prediction. In the methodology section, we give an overview to our approach and our deep learning architecture, and present the dataset used, before evaluating and discussing our results. Finally, we conclude the work with limitations and future work.

Research background

Consumers and their personality-based behavior

Personal data and its analysis have great value in electronic markets, for example for customer relationship management (Ngai et al., 2009), pricing (Rayna et al., 2015), or customer acquisition (Kazienko et al., 2013). Also, much research has shown that a customer's personality influences their consumption behavior and purchasing decisions (Barrick & Mount, 1991; Grubb & Grathwohl, 1967; Kassarjian, 1971). McElroy et al. (2007) have shown how PTs can influence online behavior. Devaraj et al. (2008) have shown that personality affects technology acceptance. Buettner (2017) showed how personality can be used to efficiently suggest products to users. In most of these works, the five-factor personality theory of Goldberg (1990) and Costa and McCrae (1992) is used to describe the different PTs of a user. In their theory, they describe the big five PTs that can be utilized to describe personality: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. These PTs are used to describe human behavior (Costa &McCrae 1992). Openness to experience describes how open a person is to new experiences and events. Conscientiousness describes the degree of determination and exactness of a person. Extraversion describes how much a person focuses their attention on external impressions. A person has a high degree of agreeableness if they are social and cooperative. Finally, neuroticism describes the degree of emotional stability of a person.

Personality-based product recommender framework

As shown, it is nothing new that the personality of a user is related to their product preference (Kassarjian, 1971). In some individual projects, systems have been developed that have shown that products can be successfully suggested to users based on their personality (Hu & Pu, 2010; Wu et al. 2013; Fernandez-Tobìas & Cantador, 2015). Based on the findings of this works, Buettner (2017) solved the "cold-start" problem, which describes the difficulty of recommending a product with no information (Hu & Pu, 2011), by predicting the personality of users based on freely accessible social network data (Buettner, 2017).

As Fig. 1 shows, Buettner's (2017) product recommender framework consists of three engines. The "retrieval and transformation engine" is designed to read the information from the social networks and convert it into a standardized vector format. By using machine learning methods, the "personality prediction engine" uses the digital footprint of a user contained in the vectors to predict their big five PTs. The "product recommender engine" uses the predicted personality to suggest matching products to the user.

Table 1 shows the evaluation accuracies of the prediction engine (Buettner, 2017). The matching is based on the scientific findings that personality influences user preferences and that these are related to product characteristics (Govers & Schoomans, 2005; Wells et al., 1957; Solomon, 1983) or the so-called product personality (Jordan, 1997). Buettner's (2017) experiment confirmed these findings, and he was able to show that the right products can be suggested to users based on their personality with greater satisfaction.

The results show that it is possible to use information about a consumer's personality to recommend products to them more successfully in terms of marketing in electronic markets. As explained in the introduction, however, social media data is subject to the problem of bias and manipulability by users (Eftekhar et al., 2014; Guleva et al., 2022), which is why a method for personality prediction is required that cannot be influenced by the user.

EEG-based personality trait prediction based on machine learning

BCIs that allow us to access the physiological data in the brain have been around for a long time, and there are many ways in which they obtain data (Rashid et al., 2020). The most commonly used method, especially in the consumer sector, are EEG-based BCIs, which can measure brain waves noninvasively using electrodes (Saha et al., 2021). These systems are based on the classical classification of the EEG frequency bands into delta, theta, alpha, beta, and gamma bands (Berger, 1929; Dustman et al., 1962; Hoagland et al., 1937; Jasper & Andrews, 1936) and use ML methods to recognize patterns in these bands for prediction (Nicolas-Alonso & Gomez-Gil, 2012). Due to the inexpensiveness and naturalness of EEG data, it is particularly suitable for use in (electronic) markets for personality prediction applications (Suzuki et al., 2019). The process of physiological signal analysis, and thus EEG-based PT prediction, can be simplified and improved by these modern ML techniques. However, due to the high complexity and dimensionality of EEG data compared to the total amount of data available, only few papers have been published in this area (Miranda-Correa & Patras, 2018). While some studies have shown a

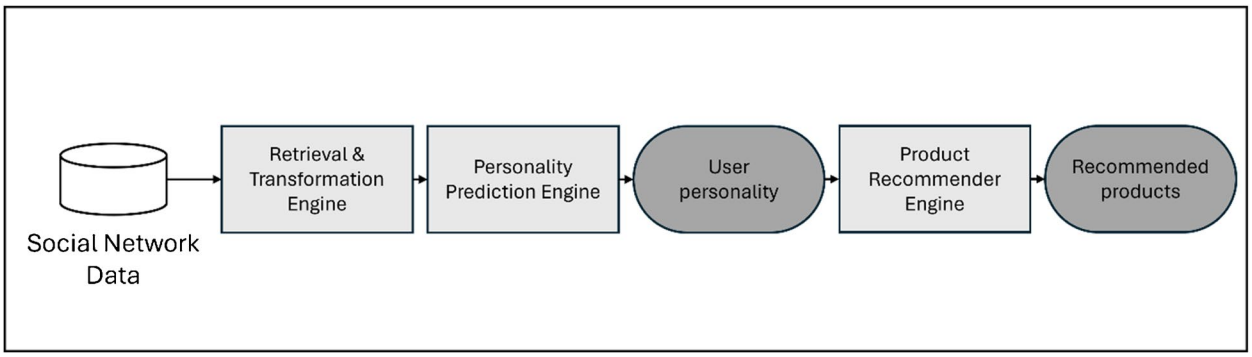

Fig. 1 Buettner's (2017) personality-mining based product recommender framework

Table 1 Evaluation accuracies of Buettner's (2017) personality prediction engine

	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism	∅
Accuracy	0.709	0.616	0.647	0.674	0.686	0.666

connection between emotional reactions and PTs, research agrees that no correlations can be identified from resting-state EEG data (Korjus et al., 2015).

Affective-state related prediction

ML methods based on affective states build on the understanding that the big five PTs are related to affective reactivity (Clark & Watson, 2008; John et al., 2008). Even if different studies show different correlations between the traits and the emotional reactions, they agree that there is a relationship between them (Finley et al., 2017; Kuppens, 2005; Letzring & Adamcik, 2015; Shiota et al., 2006). Event-related potentials (ERPs), which are EEG signals that are related to certain stimuli (Sur & Sinha, 2009), are the most widely used paradigm for emotion-based prediction with EEG signals and confirm the already known correlation (De Pascalis et al., 2004; Lou et al., 2016; Speed et al., 2015). One of the stimuli used to generate emotions are videos. In several studies, videos, which are associated with emotions, are used to measure the EEG data of the participants while watching the videos (Li et al., 2020b; Subramanian et al., 2016; Zhao et al., 2017). In this context, Bhardwaj et al. (2022) used a long-short-term memory network to predict the correlation between the generated emotional EEG data and the big five PTs with an accuracy of 90.32% (Bhardwaj et al., 2022). The authors also demonstrated another approach in which they used genetic programming to distinguish extroverts from introverts with an average classification accuracy of 71.15% (Bhardwaj et al., 2021). A cascaded network was used by Miranda-Correa and Patras (2018) to predict the PTs. The first level of the network uses a CNN + recurrent neural network architecture to determine the affective level while watching the videos. And in the second level, the PTs are predicted based on this sequence using a recurrent neural network with a mean F1-score of 0.562 (Miranda-Correa & Patras, 2018). In contrast to videos, Li et al. (2020a) used words associated with emotions as stimuli. Using a sparse regression model, they measured the correlations between the three EEG states neutral, positive, and negative and the big five PTs and showed that all five of them correlate with the emotions. What is special about the approach is that, compared to other studies, the authors chose a leave one subject out approach, whereby they were also able to show subject-independence in their model (Li et al., 2020a).

The studies show that there is a correlation between the PTs and the measured EEG data for emotions and that this correlation can be predicted using deep learning methods. However, this methodology is not suitable for use in electronic markets, as most approaches are based on subject dependency. And above all because external stimuli must be used to evoke the emotions, and no passive prediction is made in a resting-state without external stimuli.

Resting-state related prediction

Research has long sought to show the relationship between resting-state neurophysiological data and PTs. While imaging techniques such as functional magnetic resonance imaging (fMRI) have shown the correlation in individual studies (Feng et al., 2018; Nostro et al., 2018), the consensus in research is that no information regarding PTs can be recognized from resting-state EEG data (Korjus et al., 2015). Nevertheless, the fMRI results suggest that there are intraindividual correlations. But imaging procedures are not suitable for use in electronic markets compared to EGG procedures due to their costs and physical characteristics.

Eysneck (1967) put forward an early theory that human personality is related to neurophysiological data. According to his theory, the PTs neuroticism and extroversion are related to brain arousal. More specifically, extroverted people, for example, have a low level of brain arousal in the resting-state EEG (Eysneck 1967). Many studies have tried to confirm the theory by using brain arousal in the alpha band as suggested by Eysneck, but the results have been contradictory, and the theory could not be confirmed (Jawinski et al., 2021). The resting-state EEG data differ greatly between subjects, which makes a statement about correlation very difficult and leads to different results (Geissler et al., 2014). Jawinski et al. (2021) have therefore chosen an approach that includes significantly more subjects than previous studies and which, in addition to the alpha band, also includes the other bands in the analysis with brain arousal. In their study, they use resting-state EEG recordings in combination with electrooculography data and calculate the EEG vigilance score to measure the correlation between this and the big five PTs within all subjects. The study provided weak evidence that extroversion could be associated with brain arousal. A correlation was also found between openness to experience and a lower level of brain arousal (Jawinski et al., 2021). Although the work provided weak evidence for an in-sample correlation of individual PTs with EEG data, no prediction of PTs was performed and thus there is still the same consensus that PTs cannot be predicted from resting-state EEG data. Many older studies have discovered possible correlations between resting-state EEG data and one or more of the big five PTs. However, in a meta-analysis of many of these studies, Kuper et al. (2019) found that the evidence base is not robust and thus refuted the correlation, especially for the relationship between extraversion and neuroticism and frontal alpha asymmetry.

There have been some good ideas in the past that have linked PTs with resting-state EEG data. For example, Stelmack (1990) related extraversion to baseline brain arousal, but this has been refuted (Korjus et al., 2015). Attempts have also been made to link alpha band asymmetries with PTs (Coan & Allen, 2002; Davidson, 2001). However, these

results could not be confirmed in a meta-analysis (Wacker et al., 2010).

A novel approach that uses finer-graded frequency bands rather than the classical frequency bands has already been successfully applied for prediction cases in other application areas (Penava & Buettner, 2023; Penava et al., 2023), also specifically with resting-state EEG data (Breitenbach et al., 2020, 2021; Flathau et al., 2021). Baumgartl et al. (2020) used the same methodology to predict extroversion with a balanced accuracy of 60.6% using a random forest algorithm. The work has thus shown for one of the PTs that a prediction is possible, even if subject independence was not strictly considered (Baumgartl et al., 2020). Jach et al. (2020) applied multivariate pattern analysis, specifically support vector regression, to see if any of the big five PTs can be predicted from the spectral power of resting-state EEG data. Their results show that agreeableness and neuroticism can be predicted based on this, but the other PTs cannot (Jach et al., 2020).

The studies shown, that are summarized in Table 2, suggest that there could be a connection between resting-state EEG data and PTs, with individual studies even showing initial approaches to personality prediction. However, the studies also highlight the gap that calls for a subject-independent solution for applications in electronic markets that can predict the big five PTs based on resting-state EEG data that does not require any stimuli.

A meta-analysis of many published studies that have attempted to link resting-state EEG data with PTs found that the results are controversial and unclear (Vecchio & De Pascalis, 2020). Table 3 shows that there have been some attempts in the past to link PTs to resting-state EEG data, but these could not be confirmed. What the table also shows, however, is that more recent work using ML methods and newer multivariate pattern analyses has yielded promising results, and in some cases has been able to predict individual PTs based on resting-state EEG data. However, to our

Table 2 EEG studies for personality prediction/correlation

Study	Type	Goal	Subject-independence	Results
Bhardwaj et al. (2022)	Affective-state (videos)	Correlation prediction of big five PTs	/	90.32% average accuracy
Bhardwaj et al. (2021)	Affective-state (videos)	Extroversion prediction	/	71.15% average classification accuracy
Miranda-Correa and Patras (2018)	Affective-state (videos)	Big five PT prediction	/	0.562 mean f1-score
Li et al. (2020a)	Affective-state (words)	Show correlation of PTs and EEG	Yes	All big five PTs correlate with affective EEG
Jawinski et al. (2021)	Resting-state	Show correlation of PTs and EEG	No	Extroversion and openness to experience might be linked to resting-state EEG
Baumgartl et al. (2020)	Resting-state	Extroversion prediction	Partial	60.6% balanced accuracy
Jach et al. (2020)	Resting-state	Big five PT prediction	Yes	Only agreeableness could consistently be decoded. Neuroticism partially

Table 3 Different research results on the predictive power of resting-state EEG data for the big five PTs

Study	No predictive power	Partial predictive power	Predictive power
Stelmack (1990)	X (initial results were refuted)		
Davidson (2001)	X (promising results were not confirmed by the meta-analysis)		
Coan and Allen (2002)	X (promising results were not confirmed by the meta-analysis)		
Korjus et al. (2015)	X		
Kuper et al. (2019)	X		
Jach et al. (2020)		X	
Baumgartl et al. (2020)		X	
Jawinski et al. (2021)		X	

knowledge, there is currently no work that has managed to predict all of the big five PTs using resting-state EEG data.

Relevance for electronic markets

Today's society is becoming increasingly digital, and human–computer interactions play a key role in electronic markets (Raji et al., 2024). Knowledge about a user's personality can make it possible to individualize interactions in general and make them more user-friendly, improving the user experience in digital environments. The integration of personality-awareness into human–computer interaction could enable more engaging and effective user interfaces (Klados et al., 2020). With more specific reference to recommendation systems in electronic markets, in addition to Buettner (2017), several studies have empirically tested the positive influence of knowledge about a user's personality on recommendations. For example, Yusefi et al. (2018) addressed the cold-start problem of new users for recommendations. Using a questionnaire, they asked the big five PTs of a new user and clustered them based on the PTs. The new user was then recommended the items that active users from the same cluster, i.e., with similar personalities, had already rated positively. This reduced both the prediction error and improved the precision of the recommendation. In addition, Braunhofer et al. (2015) also looked at the new user problem in the scope of context-aware recommendation systems. In the context of a mobile tourism app, it was shown that the points of interest can be predicted more accurately based on the personality of a new user than with the typically used demographic attributes such as age or gender. Specifically, they have shown that with the existing information on preferences and associated personalities of active users, it is possible to "predict" the preferences of new users with their respective personalities. The personality is also determined here using self-reported questionnaires (Braunhofer et al., 2015).

To summarize, PTs are a critical factor in increasing usability and improving product recommendation systems in electronic markets. As traditional methods of personality assessment have their limitations, there is a need for alternatives for robust and accurate personality assessment. While resting-state EEG offers a promising solution, there is currently no solution predicting all the big five PTs using that data.

Methodology

In this paper, we followed the design science research approach (Hevner et al., 2004), to develop our personality prediction CNN. The five-factor personality theory of Goldberg (1990) and Costa and McCrae (1992) is the underlying theoretical basis for our approach. Buettner's (2017) personality-based product recommender system represents the scientific framework in which we will include our personality prediction CNN. Our approach corresponds to the well-established six-phase design science research framework by Peffers et al. (2007), which is also shown in Fig. 2. In the first step, we summarized the relevant literature in the research background and identified the problem that no passively observable, objective, and reliable method for assessing the big five personality traits exists for product recommendation systems. Based on this problem and the finding that personality assessment based on resting-state EEG data could be a suitable method according to previous research, we inferred and set up our objective for an automated intelligent system for this analysis. The individual objectives are derived from the problem and define that an artifact must be able to observe passively (1), must enable objectivity (2), and must allow an accurate and reliable assessment (3). In the third step, we proceeded to design the artifact based on the design objectives and developed a CNN-based architecture. In step four, we first addressed objectives (1) and (2) as proof-of-concept with exemplary data by investigating whether we can use the resting-state data as a model and then, in step 5, we checked whether and how well we can also achieve objective (3) by cross-validating the

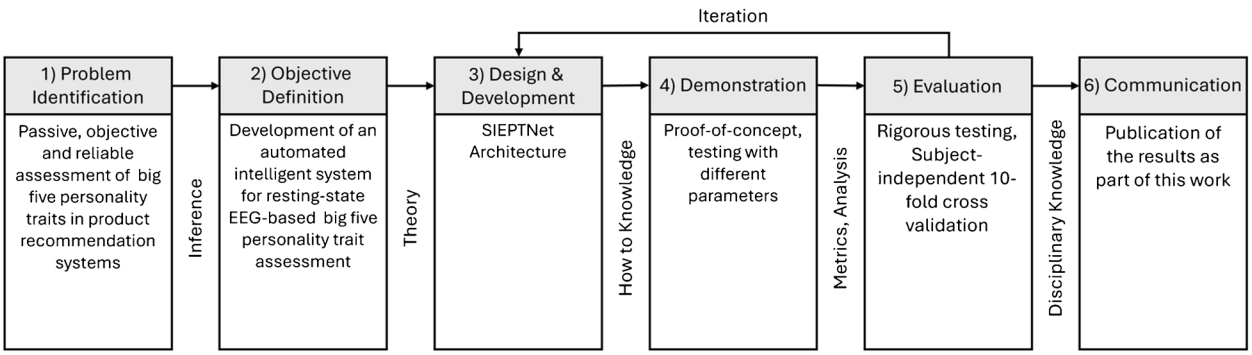

Fig. 2 Overview of our DSR process based on Peffers et al. (2007)

architecture. The evaluation has given us the opportunity to iteratively adjust the parameters of the architecture so that we achieve the individual objectives in the best possible way. In the final step, by publishing our results in this paper, we ensure that the results are publicly available to the (research) community and can be used for further research. In the following, we present the artifact and its individual components.

Resting-state EEG-based personality prediction framework

Buettner (2017) has shown in his work that his framework can efficiently suggest products based on a user's personality. Since social media data, which he uses to predict personality, is susceptible to manipulation (Eftekhar et al., 2014; Guleva et al., 2022), we propose a new sub-framework that performs the prediction using resting-state EEG data. This sub-framework is shown in Fig. 3. As illustrated, the prediction framework consists of two engines on the basis of which the user personality is predicted.

Retrieval and transformation engine

Small, portable EEG headsets that are inexpensive and suitable for consumers are nothing new (Debener et al., 2012), but the market for these wireless EEG devices has developed rapidly, and there are now an enormous number of affordable EEG devices available (Niso et al., 2023). Over the last few years, hardware has moved out of the lab environment, with more and more companies developing applications for consumers that have clear benefits for them (Wexler et al. 2019). EEG sensing technology is now being integrated into everyday objects such as headphones (Ackerman & Strickland, 2022; Chatterjee et al., 2022) and Apple, one of the largest technology companies, has also been granted a patent for the integration of EEG sensors in its earbuds (Drew, 2023). With the increasing number of devices that consumers can wear in everyday life, it is possible to record resting-state EEG data passively and automatically.

The most wireless devices have the option of storing the EEG data on the device and also providing it in real time via interfaces in ".eeg," ".vmrk," and ".vhdr" format (Niso et al., 2023). The *retrieval and transformation engine* queries this data via the API interfaces, processes it, and converts it into the correct format for the *personality prediction engine.* The engine processes the data in raw form and only applies a notch filter to remove the power line noise (Ferdjallah & Barr, 1994) and resamples the data at 250 Hz. Then, the base channel is removed from the EEG data.

Spectral analysis can reduce the complexity of EEG data by transforming the time series data into frequency domain data (Buettner et al., 2019). Within the *retrieval and transformation engine*, a power spectral density (PSD) according to Welch's approach is applied (Welch, 1967), which is implemented using the MNE library and starts at a frequency of 0.5 Hz and has no limit in the upper spectrum of the EEG bands (Gramfort, 2013). Welch's algorithm calculates the distribution of the data by using a sliding window to determine the periodogram in segments and averaging all estimates of the segments (Welch, 1967). This approach contains more information as the EEG spectrum is divided into finer sub-bands (Baumgartl et al., 2020; Breitenbach et al., 2020, 2021). The engine uses minimal preprocessing to save computational power and to be used more generally. The preprocessed data is passed to the *personality prediction engine* in ".csv" format. The CSV-file contains the pre-processed data of an individual subject per row. A row consists of 62 electrodes times 1020 frequency bands.

Overfitting is a problem that occurs when not enough data is available and the model generalizes poorly but rather learns data by memorization and thus performs well on training data but cannot be applied to test data (Ying, 2019). A possible solution to this problem is the synthetic minority oversampling technique (SMOTE), where new samples are generated based on the interpolation of neighboring instances of the minority class (Chawla et al., 2002). The

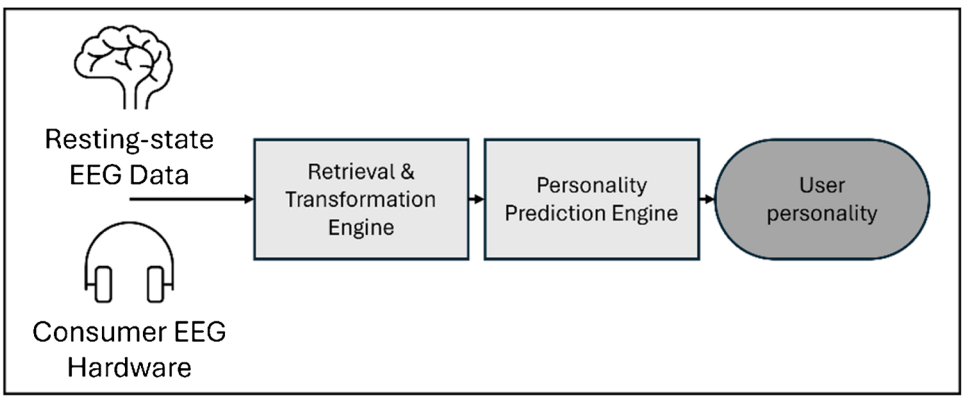

Fig. 3 Resting-state EEG-based personality prediction framework

engine therefore also applies SMOTE, implemented by the imblearn library, with the training data to compensate for the imbalance in the dataset. Nevertheless, there is still the problem that it is difficult to collect large-scale EEG data sets, which emphasizes the urgency of data augmentation for EEG data against overfitting (He et al., 2021).

Noise injection is listed as a possible augmentation method for EEG data, where a two-dimensional Gaussian noise is applied to the data to generate additional training samples (He et al., 2021). However, it should be noted that gaussian noise could destroy the temporal correlations of the EEG data, which is why it has so far only been applied to the original individual feature matrices of the EEG data (Wang et al., 2018). In our brain, there are many different signal generators (synapses, dendrites, etc.), some of which are millimeters apart but can react differently to the same stimuli and can generate a broad spectrum of frequencies (Bullock, 1990). Resting-state EEG data are therefore nonlinear by nature and tend to be characterized by chaos (Pritchard et al., 1995). There can be interactions between the individual generators which can change in seconds, minutes, or hours. A single EEG electrode receives signals from many of these generators and thus automatically captures noise (Bullock, 1990). In addition, according to Freeman and Viana di Prisco (1986), recorded EEG signals can also have three attractors. Firstly, there are resting-state attractors that occur continuously; then, there are cyclic attractors and finally there are a completely random attractors that also occur for different lengths of time and at undefined times (Freeman & Viana di Prisco, 1986). Da Silva et al. (1997) define noise signals as intrinsically random fluctuations that have a stochastic character. EEG signals recorded over time thus contain states in which noise is included (Da Silva et al., 1997). In general, however, a big part of the gross EEG data follows a Gaussian normal distribution over the time-domain and not much is known about the generation of noise in our brain and whether it may hold any crucial information content (Elul, 1969).

Most of the work using noise in EEG refer to the frequency and not the spatial domain (He et al., 2021). There are many different types of noise in the human brain. On the one hand, sensory noise can occur, which can be caused by odors or light. Electrical noise can also be generated by random membrane potentials. General synaptic noise has also been observed, as different EEG signals were measured in the same person even though the exact same stimuli were given several times. Noise is thus omnipresent in the EEG, and it has been shown that the noise level estimation can be performed with a Gaussian process (Faisal et al., 2008).

In other domains, it has been shown that noise can negatively influence the robustness of ML models as it is an exception to the norm (Xu et al., 2014). Since in this work we try to develop a subject-independent CNN that predicts the PTs of a subject based on its EEG, we try to make the model independent of individual characteristics such as noise. The central limit theory states that the distribution of sample means adapts to the normal distribution as the quantity increases, which can also be transferred to the distribution of noise (Kwak & Kim, 2017). As shown before, the distribution of noise according to this principle is covered in many systems by the Gaussian distribution (Park et al., 2013).

To summarize, noise in the EEG data arises individually from several sources depending on the subject. It is not known to what degree information content is contained in the noise, but that parts of it can be explained by a Gaussian distribution. In this paper, we hypothesize that because the noise is so individual and assuming that there is no information about PTs in it, the subject-independent predictive power of EEG-based CNN models for PTs becomes more robust when the noise in the model's training data is smoothed by a Gaussian distribution. This would reduce the individual component of noise from the data and ensure that the data is less subject-dependent, and the model can generalize better.

In the *retrieval and transformation engine*, a special innovative implementation of a one-dimensional Gaussian filter is therefore used as the last step to try to reduce the noise in the data, in contrast to noise injection. Since the engine removes the temporal domain from the data in the previous steps using spectral analysis, we do not run the risk of destroying temporal dependencies using the Gaussian filter. The classic one-dimensional Gaussian filter of the SciPy python package is used for noise reduction. The innovation within our implementation is that we do not run the filter over the entire data at the same time but use the individual data of the single electrodes. This ensures that the noise is only smoothed across the frequency bands within an electrode and not across several electrodes and thus across the spatial dimension. The procedure is based on the fact that noise in EEG mostly refers to the frequency and not the spatial domain (He et al., 2021). The procedure is only applied to the training data, which doubles the number of samples, as training is carried out with both the original and the augmented data.

Personality prediction engine

The *personality prediction engine* receives the minimally preprocessed data, which on the one hand contains the PSD values of an individual subject and its values for the big five PTs per row. The spectral analysis has reduced the complexity of the data by removing the temporal domain. This allowed us to choose a simpler architecture, as no temporal dependencies need to be considered, as is the case with recurrent neural networks, for example. Compared to

Baumgartl et al. (2020) who built on a simpler ML approach to predict partially subject-independent PTs based on EEG data, we use a newly created CNN architecture called Subject-Independent EEG-based Personality Trait Network (SIEPTNet), which is shown in Fig. 4. For most applications, artificial neural networks such as CNNs outperform simpler ML approaches (Janiesch et al., 2021).

SIEPTNet is a sequential CNN consisting of a total of 13 layers. The input vector of SIEPTNet is one-dimensional and contains 63,240 features corresponding to the 62 EEG channels times the 1020 frequency bands per channel. All three convolutional layers are one-dimensional and have a kernel size of three with 64 filters. Each of the convolutional layers is followed by a batch normalization layer. Layers 5, 9, and 10 are each max pooling layers with a pool size of two and where padding is permitted. A dropout layer with a rate of 0.8 is added after the first and third max pooling layer to avoid overfitting. The last two layers are a standard flat layer and finally a fully connected dense layer with a single output unit and a sigmoid activation function.

The model is compiled with an Adam Optimizer (Kingma & Ba, 2014) and a fixed learning rate of $1e^{-4}$ using a binary cross-entropy loss function. A binary classifier model is trained for each of the five PTs so that the weights of the model can adapt to the PT in each case. The SIEPTNet architecture is orientated towards EEGNet, a compact CNN for the classification of EEG data (Lawhern et al., 2018). However, SIEPTNet is a one-dimensional CNN which is specialized in the classification of EEG data pre-processed by spectral analysis. The output of the model is a binary decision for the respective PT. The five decisions for the user's PTs are available after the *personality prediction engine.*

User personality

The personality of an individual user was predicted by the proposed framework using the five PTs. No information about the respective user was required in advance and the framework determined their personality completely independently of the individual subject. The information about the PTs can then be used in the product recommendation framework by Buettner (2017) to better recommend products to the user. In comparison to the stage where no information about the PTs of a user is available, we can only guess the user's personality, which is correct with a probability of 2^{-5}. The results shown later demonstrate that we can increase this probability from 3.125 to 12.53% with our framework and thus achieve a 4 times higher probability in predicting the personality of a particular user.

Personality-based product recommendation framework

Our developed artifact utilizes consumer hardware devices for EEG measurement as part of the recommendation framework. Due to their increasing availability and the ever-easier integration into everyday life, they represent a passive way of measuring the resting-state EEG (Drew, 2023) and

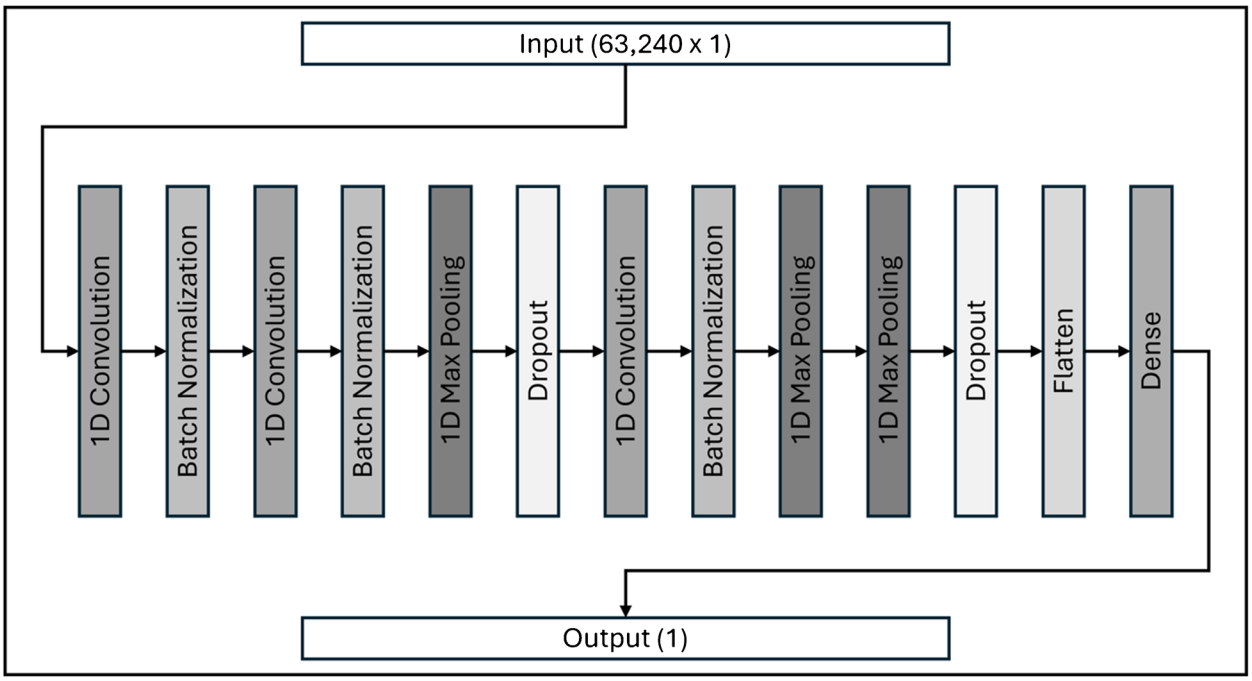

Fig. 4 SIEPTNet architecture

thus contribute to the fulfillment of the design objective (1). Resting-state EEG data contributes to the fulfillment of the second research objective of objectivity (2) due to their characteristics of not being manipulable by the user and thus being unbiased and not dependent on an external reviewer (Brocke et al., 2013). Through rigorous evaluation using tenfold cross-validation and the demonstrated performance increase from 3.125 to 12.53%, we also fulfill the third objective for accurate and reliable assessment (3). At this point, we have developed an artifact with which the personality of a new user can be predicted. This knowledge can be embedded in a recommender framework in different ways. On the one hand, the PTs can be matched with product characteristics, which in turn are assigned to PTs, and suggestions can be made based on the match (Buettner, 2017). Another option is to cluster existing users whose purchasing decisions are already known according to their personality and then integrate new users into the clusters (Yusefi et al., 2018). And a matrix factorization-based recommendation algorithm could be developed based on known users and their personality and preferences (Braunhofer et al., 2015). All three methods have successfully shown that knowledge about the PTs of a new user can be used to recommend products more efficiently.

Validation procedure

To validate our framework, we first pre-processed the entire data as described using spectral analysis and merged it into CSV format with the PT scores. We then applied a stratified k-fold to split the data into ten train-test splits. The evaluation in several independent folds helps to ensure that the model and the results can be generalized and are not based on lucky splits. In K-fold cross-validation, the data is divided into K segments of equal size, one of which is left out for testing in each iteration (Breiman, 1996). The procedure was performed individually for each of the five PTs and a random state of 42 was used for data splitting to have the same data for each PT in each split for comparability. For each split, we then performed SMOTE only with the training portion to have a balanced training set. We then applied a standard scaler to the training data and subsequently transformed the values to the test data. Further, we used the training data to train the model with a batch size of 16 and 200 epochs. We used a callback which saves the epoch with the best validation accuracy to be able to retrieve the best model at the end. After the training of the model was finished, we have evaluated it with the test data. We reported the following values: accuracy, balanced accuracy, F1-score, true positive rate (TPR), true negative rate (TNR), positive predictive value (PPV), negative predictive value (NPV), area under the curve score (AuC), and prevalence. In addition, we generated a confusion matrix for each fold. We then performed the same procedure again with the same random state for the splits, with the modification that after applying SMOTE, we additionally applied our gaussian filter to the training data to double it. By using the same random state, we were then able to compare whether the use of our innovative filter led to better results. The procedure shown ensures that we achieve valid results for a subject-independent prediction of the PTs.

Dataset

To demonstrate the quality and reliability of our approach, we utilized an extensive dataset of EEG data that is widely used in the scientific community. The data we used is part of the Leipzig Study for Mind–Body-Emotion Interactions (LEMON) dataset (Babayan et al., 2019). This dataset includes publicly available resting-state EEG data from 203 participants whose data was tagged using 62 digitized EEG channels. The study underlying the data was conducted in accordance with the Declaration of Helsinki. The protocol used was also approved by an ethics committee. Prior to the study, each participant was required to provide written consent that they agree to the anonymized sharing of their data. The dataset can be used freely under the Creative Commons Attribution 4.0 international license. For each participant, 16 min of resting-state data were recorded, eight with eyes closed and eight with eyes open. In addition to the EEG data, the dataset also contains the assessment of the NEO-FFI personality survey of the individual subjects. The assessment was carried out using a 5-point Likert scale, with values ranging from 0 (strong denial) to 4 (strong approval) (Babayan et al., 2019). In order to generate a binary decision from the assessment of the five PTs, we calculated the mean score for the individual values for all subjects and then grouped the subjects according to this score. The mean scores are given in brackets: neuroticism (1.50), extraversion (2.41), openness for experiences (2.69), agreeableness (2.75), and conscientiousness (2.67). By grouping the subjects according to the mean scores, a certain imbalance has emerged within the individual PTs. Table 4 provides an overview of the distribution within the classes.

Results

The results of the validation process are shown below. Table 5 first shows the evaluation metrics of the model evaluation. These are the average scores of each criterion across the ten folds. Table 5 shows the results for running the model without applying the developed Gaussian filter.

In comparison, Table 6 shows the average evaluation results of the run in which the Gaussian filter was used for data augmentation. Table 5 shows that our new SIEPTNet architecture achieves a significant predictive gain for each of the PTs in balanced accuracy (i.e., predictive power) on

Table 4 Class distribution within the personality traits

	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Yes (over mean score)	104	100	114	108	90
No (under mean score)	107	111	97	103	121

Table 5 Average evaluation metrics over 10 folds without Gaussian filtering

	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Accuracy	0.6069	0.6400	0.6394	0.6779	0.6208
Balanced accuracy	0.6109	0.6391	0.6329	0.6851	0.6121
F1-score	0.6537	0.5711	0.6551	0.7074	0.4927
TPR	0.8700	0.5255	0.6992	0.8300	0.5556
TNR	0.3518	0.7527	0.5667	0.5402	0.6686
PPV	0.6080	0.7658	0.7000	0.6341	0.5700
NPV	0.8899	0.6055	0.6632	0.8253	0.6694
AuC	0.5623	0.5836	0.5723	0.6296	0.5901
Prevalence	0.4929	0.5119	0.5403	0.4740	0.4266

Table 6 Average evaluation metrics over 10 folds with Gaussian filtering

	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Accuracy	0.6403	0.6398	0.6818	0.6874	0.6539
Balanced accuracy	0.6436	0.6391	0.6684	0.6897	0.6607
F1-score	0.7155	0.6390	0.7231	0.6922	0.6054
TPR	0.9036	0.6673	0.7856	0.7400	0.7111
TNR	0.3836	0.6110	0.5511	0.6394	0.6102
PPV	0.6008	0.6882	0.6992	0.6799	0.5801
NPV	0.8273	0.7033	0.6923	0.7402	0.7996
AuC	0.5617	0.5664	0.5490	0.6428	0.5647
Prevalence	0.4929	0.5119	0.5403	0.4740	0.4266

average across all folds compared to the random guess. Table 6 then additionally shows that with the innovative Gaussian filter a further predictive gain could be achieved for each PT except for conscientiousness. Figure 5 shows the comparison between the confusion matrices, which on the one hand shows the values averaged over the folds for the run without Gaussian filter, as well as the average values for the run with Gaussian filter. This also confirms the previous observation that the Gaussian filter increases the predictive power and further improves the classification results.

Discussion

The results presented show the potential of EEG data for the prediction of PTs. The presented *personality prediction engine* should be able to be integrated into the framework of Buettner (2017) without performance losses. For this reason, Fig. 6 shows the comparison of the results achieved by the existing engine compared to the results shown. Buettner (2017) reported the accuracy for the prediction engine in his work. To compare the results, we also calculate the balanced accuracy due to the imbalance of the data set, which is calculated from the arithmetic mean of the sensitivity and specificity (Dinga et al., 2019). Balanced accuracy is often used to evaluate imbalanced datasets (Brodersen et al., 2010).

The comparison in Fig. 6 shows that EEG data is a suitable substitute for the social media data in Buettner's (2017) product recommender framework. In a direct comparison, the balance accuracy of the EEG data outperforms the values of the social media data for each of the five PTs. In addition to the superior results, EEG data also has the advantage over social media data that it cannot be manipulated in contrast to user behavior on social media and does not change over a lifetime (Brocke et al., 2013; Costa & McCrae, 1992; Romero et al., 2009).

Epistemological discussion

The majority view in research assumed that there is no correlation between resting-state EEG data and the big five PTs,

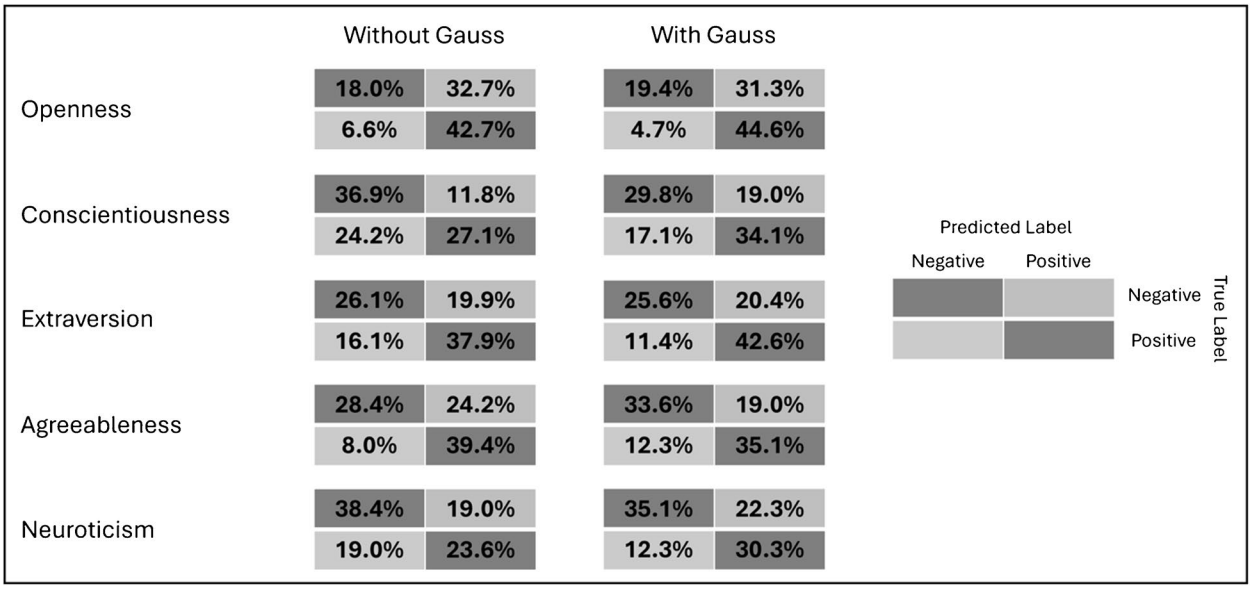

Fig. 5 Confusion matrices of all PTs

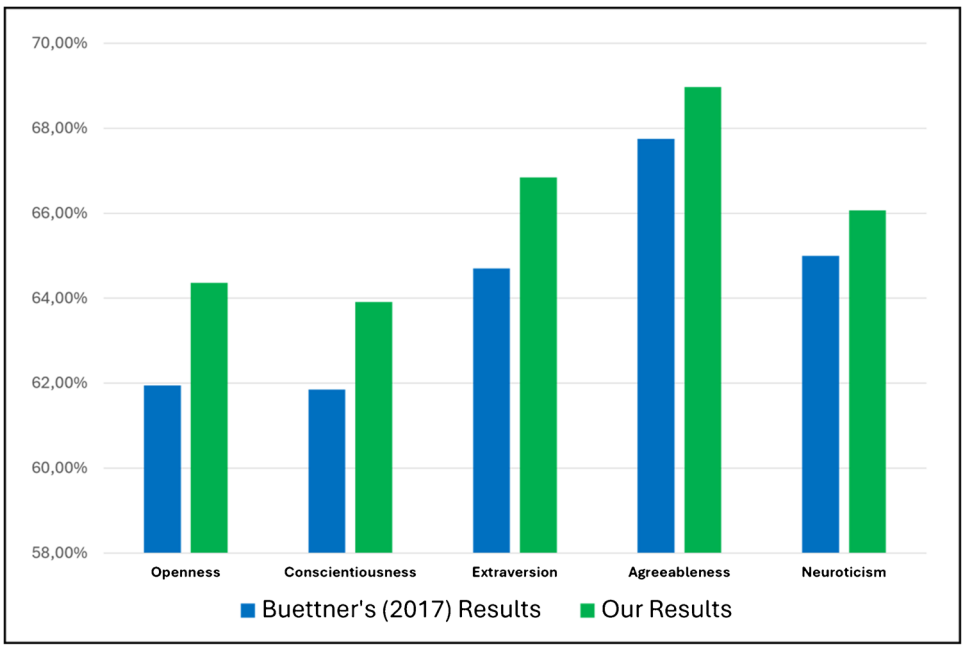

Fig. 6 Comparison of the balanced accuracies of both approaches

and it is therefore not possible to predict PTs based on this data (Korjus et al., 2015). However, the timeline in Fig. 7 also shows that recent work has achieved promising initial results in predicting individual PTs, although no work has been successful with more than two PTs. One reason for the nevertheless positive results could be the use of more modern ML methods, with which more complex multivariate pattern analyses can be carried out (Jach et al., 2020). Compared to the simpler ML methods, we have used a neural network for the prediction. Such deep learning methods outperform simpler ML methods in most use cases, as they can learn far more complex patterns (Janiesch et al., 2021). Our results show that the approach was successful, and that for the data available to us we have refuted the assumption that there is no correlation between the PTs and resting-state EEG data. To our knowledge, this makes us the first paper to successfully predict all five PTs. In addition, we were able to increase the predictive performance of our model for almost all PTs by applying our innovative Gaussian filter and thus significantly increase the subject-independent classification of the PTs. We suspect that by applying the filter we were able to remove the subject-individual noise from the EEG

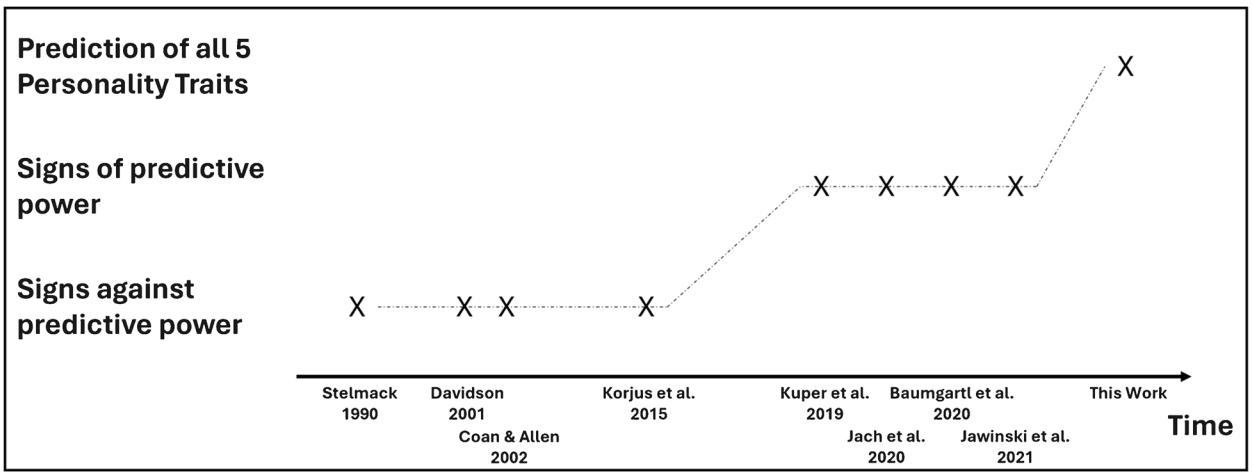

Fig. 7 Research on predictive power of resting-state EEG data for PTs over time

data and thus make the data basis more robust. This leads to the assumption that the noise does not contain any relevant information about the PTs, as the performance of the model increases with its removal. However, this assumption is not proven by this work, but merely represents an observation that needs to be confirmed by future research.

Practical discussion

The information about a subject's PTs is collected via BCIs in combination with our demonstrated methodology. This information can be used profitably in various ways. Van Erp et al. (2012) have identified seven areas of application for BCI applications in the industrial sector. The seven areas are as follows: device control, user state monitoring, evaluation, training and education, gaming and entertainment, cognitive improvement, and safety and security. Device control describes the control of any industrial devices or machines and enables their remote control, for example. User state monitoring describes the possibility of tracking a user's states such as fatigue, stress, workload, etc. Evaluation simply means using the brain's data, e.g., for neuromarketing purposes, whereas training and education describes applications that utilize the brain's ability to change and adapt. BCIs also represent a new application platform for the gaming and entertainment industry. Cognitive enhancement describes applications that adapt a subject's brain activity based on neurofeedback, for example to increase agility. Safety and security BCI applications can increase general safety by, for example, tracking a user's arousal state and, in some cases, recommending a break (Van Erp et al., 2012). Information about a subject's personality can add great value in each of these areas.

Starting with evaluation, the information about the PTs can be used for more efficient (neuro-) marketing. Buettner (2017) has shown that this information can be used in electronic markets for better product recommendations and can thus increase the profitability of a company. The personality of a subject influences their way of learning and therefore has a direct influence on the education industry. Although to varying degrees, all of the big five PTs have an influence on a subject's education and learning (De Raad & Schouwenburg, 1996). In particular, the openness PT is associated with the type of learning and learning goals, while the conscientiousness trait is associated with academic achievement (Jensen, 2015). Different subjects therefore need different learning programs. Knowledge of PT enables the design of individualized learning experiences, which has been a desired goal in education for several years and is increasingly possible through the electronic domain (Tetzlaff et al., 2021). Gaming and entertainment is a big part of electronic markets. A gamer's personality can determine their choice of game genre and also influence their compulsive buying behavior. A game developer can therefore use the information about a gamer's PTs to develop a better marketing strategy for the game's online sales (Jin et al., 2023). Also, the gamers personality can be used a more individual game design in the entertainment industry (Peever et al., 2012). When it comes to operating machines (device control), there are three different personality types which are related to the big five PTs, among others. One of the types, for example, is the stressed operator, who needs different instructions in difficult situations than a more relaxed operator. Knowledge of the PTs can therefore make the operation of devices more efficient (Strubelt et al., 2019). In general, regarding device control, it is important to emphasize that personality plays a major role in the use and acceptance of human–machine interfaces by operators and that knowledge of the PTs is therefore of great benefit in this context (Stowers et al., 2017). BCIs also allow remote control of devices, enabling remote working in

this sector. The big five PTs are also related to remote work exhaustion and can be useful in predicting it. For example, neuroticism is a predictor of exhaustion, while agreeableness and conscientiousness are protectors (Parra et al., 2022). The big five PTs can also be an indicator of how well a person performs a job and how well that job fits the person (Barrick & Mount, 1991). Likewise, some work-related traits such as work self-efficacy or satisfaction can be related to PTs, such as extroversion in this case (Van den Berg & Feij, 2003). It has also been shown, for example, that variability in extraversion in group tasks increases the performance of the whole group (Kramer et al., 2014). Cognitive improvement can be used to train and improve certain characteristics of a subject (Van Erp et al., 2012). If you know the PTs of a user, you can design cognitive improvement specifically for them so that they perform better on the job or a work group fits well together, although ethical issues must be considered here. PTs also influence how a person deals with and reacts to situations such as stress (Vollrath, 2001), attention or the (perceived) workload (Rose et al., 2002). For example, people with a high level of agreeableness and conscientiousness need social activity after a stressful event, while neuroticism, for example, is generally associated with traumatic stress (Hengartner et al., 2017). So, if a user's condition is monitored using BCIs, it is important to know the PTs of this person to define appropriate measures and thresholds for exceptional situations. This information is also valuable in the context of safety and security related BCI applications that are closely linked to user state monitoring applications. In addition, the personality of a subject also has a direct influence on their perception of safety. For example, conscientiousness and openness are two traits that correlate positively with process control performance (Burkolter et al., 2009). Especially in the electronic age, information security is of great relevance and PTs represent a major risk factor here in particular. Conscientiousness, for example, is a major indicator of positive activity towards information security (Uffen & Breitner, 2013).

Practical concerns

The practical added value of a tool for predicting a user's PTs is relatively clear for all the areas of application of BCIs mentioned. However, before such a tool can be used in practice, important questions need to be clarified. The first aspect is that there are no security standards for BCIs and for consumer hardware for reading EEG data, thus paving the way for cyber-attacks and data manipulation (Bernal et al., 2021). Theoretically, such applications can be used to intercept and analyze a user's raw EEG data, which raises major concerns in data protection (Takabi et al., 2016).

Even if novel deep learning architectures like ours support decision-making, there are methodological drawbacks involved. One of the most important drawbacks is the dependency on more data to optimize the models (Ahmed et al., 2023). Especially with EEG data, this is a major problem, as existing data sets are difficult to obtain. For these reasons, we have developed a very efficient model that works subject-independently and thus delivers promising results. Nevertheless, the model and its further development is also dependent on additional larger data sets, which would increase the training time. Another aspect is the difficulty of interpreting deep learning models and the associated problem of being able to understand the decisions made by them. When implementing the artifact, the design principle should therefore be to use "white-box" approaches to ensure that the decisions are transparent (Rieg et al., 2020).

Ethical concerns

In addition to practical concerns, considerations of the ethical aspects of brain-reading technologies are an exceedingly important aspect in the implementation of the artifact shown. In his work on the rise of these technologies, Drew (2023) posed a risk to cognitive freedom and mental privacy. Brain data, in relation to other people related data, can reveal very intimate information about a human. An important aspect is that information that can be derived from the brain is directly linked to the human being who produces it, but at the same time, the individual cannot easily control it (Ienca & Andorno, 2017). Brain reading technologies that exploit a person's inner thoughts jeopardize people's right to cognitive freedom, highlighting the urgency for legislative reform before such applications are implemented (Farahany, 2012). Ienca and Andorno (2017) therefore propose four new laws to protect cognitive liberty, mental privacy, mental integrity, and the right to psychological continuity. These four new laws are designed to ensure that individuals retain the autonomy to control their mental states and reject neurotechnological interventions, prevent unauthorized access to brain data, and avoid manipulation of neural processes. And also to ensure that an individual's sense of identity is protected (Ienca & Andorno, 2017). Compliance with such proposed laws is particularly important for applications that use peoples brain data regarding their personality for marketing purposes. When implementing such an application, it is therefore essential to pay attention to design principles that deal with these rights, for example by using homomorphic encryption to protect personal information from exploitation (Popescu et al., 2021), or, for example, by having the models for evaluation only process the information locally at the persons premises and not uploading the brain data at all and processing it online (Xu et al., 2022).

If the capabilities of brain reading technologies continue to develop in this way, Kantian and privacy concerns could

materialize. In industry, the prediction of consumer behavior could give the impression that consumers are things without dignity and cognitive freedom. In the sense of Kantian ethics, people would then only be objects for the purpose of marketers. However, the artifact we have developed is probabilistic and the consumer retains free will and will probably never be completely predictable, which makes Kantian concerns unrealistic. Nevertheless, this makes it even more important for companies to be completely transparent in such applications and to create maximum opacity in consent, data use and overview of the applications capabilities to ensure the dignity of the human being and their free cognitive will (Stanton et al., 2017).

Conclusion

Based on the finding that traits are related to biological factors such as genes (Romero et al., 2009), we initially hypothesized that PTs must be detectable in a subject's resting-state EEG data. By building on Buettner's (2017) personality prediction engine and creating a way to predict all five PTs using resting-state EEG data, we were able to confirm this hypothesis for the dataset used.

The results obtained for all five PTs show that in a future with an increasing number of consumer-graded EEG hardware, which will enable electronic markets to access user-related EEG data, the EEG data represents an alternative to the social media data in Büttner's (2017) product recommender framework. Beyond the framework, we have also shown that there is great economic potential for the resting-state EEG-based personality prediction engine in various industries.

Limitations and future work

The personality prediction engine is based on the fact that PTs do not actually change over a person's lifetime and remain stable (Costa & McCrae, 1992). We take this assumption as valid and therefore expect to predict the PTs in the EEG data over the measured period of the dataset. In future research, however, we want to test this assumption and try to falsify it by having our engine predict several individual time periods of the EEG from one subject and investigating whether the same result is predicted in each case or whether it changes over time.

In our work, we have presented and tested a new deep learning architecture for the analysis of EEG data. In future work, we will systematically test further architectural possibilities such as 3D CNNs or 2D CNNs to create comparisons to the proposed 1D architecture (Craik et al., 2019). Last but not least, the personality prediction engine we proposed should be integrated and tested in various real-world electronic markets scenarios, which we proposed among others, in order to improve it.

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Data Availability The complete LEMON Data can be assessed via Gesellschaft für wissenschaftliche Datenverarbeitung mbH Göttingen (GWDG) https://www.gwdg.de/. Raw and preprocessed data at this location is accessible through web browser https://ftp.gwdg.de/pub/misc/MPI-Leipzig_Mind-Brain-Body-LEMON/ and a fast FTP connection (ftp://ftp.gwdg.de/pub/misc/MPI-Leipzig_Mind-Brain-Body-LEMON/). In the case the location of the data changes in the future, the location of the dataset can be resolved with PID 21.11101/0000-0007-C379-5 (e.g. http://hdl.handle.net/21.11101/0000-0007-C379-5).

Declarations

Competing interests The authors have declared that no competing interests exist.

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