Automatic Personality Prediction: A Systematic Mapping Study

Khaoula Chraibi
Computer Science department
Faculty of Sciences and Technologies,
University of Sidi Mohamed Ben Abdellah
Fez, Morocco
khaoula.chraibi@usmba.ac.ma

Ilham Chaker
Computer Science department
Faculty of Sciences and Technologies,
University of Sidi Mohamed Ben Abdellah
Fez, Morocco
ilham.chaker@usmba.ac.ma

Azeddine Zahi
Computer Science department
Faculty of Sciences and Technologies,
University of Sidi Mohamed Ben Abdellah
Fez, Morocco
azeddine.zahi@usmba.ac.ma

***Abstract— Context*: Automatic Personality Prediction has experienced significant growth and has appealed to researchers thanks to its useful applications. However, as far as we are aware, there is a lack of studies that summarize systematically the different works in literature. – *Objective*: To describe the current state of the art, specifically to: (i) determine the demographic characteristics of the studies published in this topic, (ii) identify the used psychological models, (iii) characterize the prediction approaches in terms of methods, data and features. - *Method*: We conducted a systematic mapping study by following a recommended process. We employed an automatic search in different well-known databases and applied selection criteria to obtain the final set of papers to be studied. Then we proceeded to the extraction of specific information from selected papers to answer our questions. - *Results*: We evaluated 379 articles. The results show that the number of primary studies has increased significantly. We identified the trends concerning: personality models, data inputs and sources, prediction types, methods and features. - *Conclusion*: This overview of the literature may be a solid and comprehensive baseline for researchers in the domain of personality prediction. It may assist in identifying research directions and potential paths to explore.**

Keywords— Affective computing, automatic personality perception, automatic personality recognition, systematic mapping study

I. BACKGROUND

A. Personality Psychology

Personality refers to 'individual differences in characteristic patterns of thinking, feeling and behaving' [1]. The study of personality has a broad and diversified history in psychological science with an abundance of theoretical perceptions. The main theories include the psychodynamic perspective, humanistic, biological, behaviorist, evolutionary, and social learning perspectives [2], [3]. One of the most prominent trends today is the dispositional (trait) perspective (which is based on the descriptions we use in our daily lives to describe characters) and it is one of the most important achievements of psychology [4]. This diversity of psychological approaches led to the production of several models to assess personality, some of them are [3]:

- 16 Personality Factors (16 PF): Developed further by Raymond Cattell describing 16 trait dimensions. These traits are warmth, reasoning, emotional stability, dominance, liveliness, rule consciousness, social boldness, sensitivity, vigilance, abstractedness, privateness, apprehension, openness to change, self-reliance, perfectionism and tension.
- PEN: Hans Eysenck adopted three dimensions' personality model, which are Psychoticism P, Extraversion E and Neuroticism N (PEN).
- The Big Five personality traits (Big5): created by Paul Costa and Robert McCrae, Big5, the five-factor model or also the OCEAN model organizes all personality traits along a continuum of five factors: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism.
- The Myers-Briggs Type Indicator (MBTI): The MBTI scale, developed by Katharine Cook Briggs and Isabel Briggs Myers, provides a broad variation in personality classification by providing four personality classes: Extroversion/Introversion, Sensing/Intuition, Thinking/Feeling, and Judging/Perceiving. The combination of these classes provides 16 MBTI personality types.

Several other models exist, like DISC (Dominance, Influence, Stability and Compatibility), Dark Triad (Narcissism, Machiavellianism, and Psychopathy traits), Keirsey Temperament (Artisan, Guardian, Idealist and Rational temperaments), etc.

The assessment of an individual personality can be done through two methods: the first one is based on interviews conducted by a psychologist who evaluates the personality according to his observation and/or tests. The second is the personality inventories. They consist of several statements that reflect particular ways of acting, thinking or feeling, and use multiple-choice items or numbered scales, represented by a range from 1 (strongly disagree) to 5 (strongly agree). The questionnaire is filled by the person itself (self-report), or by other people (other-report). There is a wide variety of tests, like Myers-Briggs Type Indicator (MBTI), Sixteen Personality Factor Questionnaire, NEO Personality Inventory.

Both methods require human intervention and cooperation, which may cause bias in results. Moreover, this task requires rigorous effort and is time-consuming. On the other hand, personality affects individual choices and preferences, which are very important pieces of information in several domains. Given

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these facts, a new branch in computer science arises intending to study the personality automatically. This domain is Personality Computing.

B. Personality Computing

Personality computing is the combination between artificial intelligence (computer science) and personality psychology (psychology). It studies personality through computational techniques. Mainly, it addresses three problems: automatic personality recognition (APR), perception (APP) and synthesis (APS) [5].

APR recognizes the true personality of an individual, which is the self-reported personality. APP predicts the personality others attribute to a given individual (other-reported personality). Finally, the purpose of APS is the generation of artificial personalities in embodied agents [5].

The scope of this work solely pertains to APR and APP, which we will refer to by 'automatic personality prediction' (APPR) in the remainder of this paper.

APPR uses different digital footprints from several sources to infer personality, such as text, video, audio and social media. The relation between these traces and personality is widely studied to identify possible correlations and to give evidence to such researches [6], [7], [8], [9]. The prediction is mostly done by means of machine learning techniques, namely classification and regression methods. To test and validate the performance of those methods, self-assessed personality tests or observer ratings are always exploited as the ground truth.

The importance of this research field is emphasized by its use in different areas. In the following, some examples of its applications [10], [11], [12], [13]:

- Education: Personalized learning strategies, Student career prediction and guidance, Tutoring/training systems;
- Medicine: Specialized health care and counseling, Diseases detection;
- Recommendation systems: Dating suggestion, Friend, Music, E-Commerce, Movies and Job recommendations;
- Forensics: Lie detection, Deception detection, Fraud detection, Criminal identification, Terrorist detection;
- User experience: Enhanced Personal Assistants, Personalized user interfaces, Modeling social robotics, Virtual reality, Gaming, Chatbots;
- Marketing: Advertising, Customer care;
- Word polarity detection: Sentiment analysis, Cyberbullying detection, Sarcasm detection;
- Other: Psychological studies, Political forecasting, Authorship identification, Employee Recruitment, Emotion detection.

C. Objectives of This Review

The domain of personality computing has known tremendous growth in the last decade. However, as far as we are aware, there is no systematic review or mapping that covers trends and research directions in APPR. Given this lack of secondary studies, we consider that conducting a Systematic Mapping Study (SMS) in this topic is important and justified. To fill this gap and give a comprehensive overview of the current state of the art, we have designed 4 high-level Research Questions (RQs) with a total of 9 sub-questions as a guide to this SMS (see TABLE I).

TABLE I. RESEARCH QUESTIONS OF THE SMS

Research questions	Sub-questions
RQ1 What are the demographic characteristics of the studies about automatic personality prediction?	RQ1.1 When are the studies published? RQ1.2 Where are the studies published? RQ1.3 How publications are geographically distributed?
RQ2 Which personality models are used?	
RQ3 What are the characteristics of the input data?	RQ3.1 What types of data are used? RQ3.2 Which are the sources of data used?
RQ4 What are the characteristics of prediction?	RQ4.1 Which category of personality prediction is used? RQ4.2 What prediction methods are used? RQ4.3 What are the categories of the used methods? RQ4.4 What are the types of features used for the prediction?

II. REVIEW METHOD

In order to conduct this review, we broadly followed the guidelines by Kitchenham and Charters [14]. We first performed a search and selection process to obtain the primary studies that constituted the basis for our mapping. Next, information related to personality models, input data and prediction methods were extracted from the primary studies. Finally, we synthesized the data to obtain the results of the review.

A. Identification of Research

1) Search String Construction

The search process in our SMS aims to find as many primary studies related to the RQs as possible using an unbiased search strategy. To construct the search string, we first identify the main terms, which are: 'Personality' and 'Prediction'. Then we collected all possible synonyms from the preliminary search in the topic. After some trials, we choose the terms cited in TABLE II. Using these terms and the booleans OR and AND operators, the search string is as follow:

(Analysis OR Analysing OR Analyzing OR Assessing OR Assessment OR Classification OR Classifying OR Computational OR Computing OR Detecting OR Detection OR Determining OR Estimation OR Extracting OR Extraction OR Identification OR Inference OR Inferring OR Perception OR Predict OR Predicting OR Prediction OR Recognizing OR Recognising OR Recognition) AND Personality

2) Literature Resources Identification

Using the defined search string, an automatic search is performed on the databases of IEEE Xplore, Scopus, as well as Web of Science. The databases have been selected based on some criteria reported by Napoleão et al. [15] such as (i) coverage (a large number of conferences proceedings and journals in computer science domain); (ii) quality of results (the papers obtained are indexed); and (iii) versatility to export (a mechanism to export the results of the search is available). Other popular databases (e.g. ACM DL) are not included because most of their results are returned by Scopus.

As recommended by Kitchenham [14], we have used tools for managing the references extracted from the databases, specifically, EndNote [16] and Qiqqa [17].

B. Study Selection

In order to select the set of relevant papers, we have designed a study selection process inspired from [18] and [19]. This process consists of a set of phases as shown in Fig. 1.

Every selection phase is based on inclusion and exclusion criteria, which are as follow:

Inclusion Criteria:

- Papers are primary studies;
- Studies are in the computer science field;
- Studies are reporting an automatic personality prediction method;
- Studies are published in peer-reviewed journals, conferences, or workshops;
- Papers are published until April 2019.

Exclusion criteria:

- Papers are secondary or tertiary studies;
- Papers are not written in English;
- Studies are not freely accessible to the authors in full-text;
- Duplicated studies (In such a case; we included the most recent one, or journal paper rather than proceeding.);
- Studies using personality as input or using existing APPR methods.

In the rest of this section, we provide the details of each study selection process phase shown in Fig. 1.

Phase 1. Automatic Search: We employed our search string on the three selected databases. The search was limited on title, abstract and keywords. As a result, we obtained 687 532 papers. TABLE III shows how many studies have been extracted per database (see column Search results).

Phase2. Automatic Search with Filters: as the number of returned results was very important, we used the available filters in every database to reduce noise and irrelevant papers. TABLE III shows the filters we have used in each database and the resulting number of articles after applying them (see column Filtered search results). As a result, the total number was reduced from 687 532 to 8 407.

Phase3. Duplicates removal: By using the reference manager EndNote, 2 670 duplicates were detected and removed automatically. After this step, we ended up with 5 737 remaining papers.

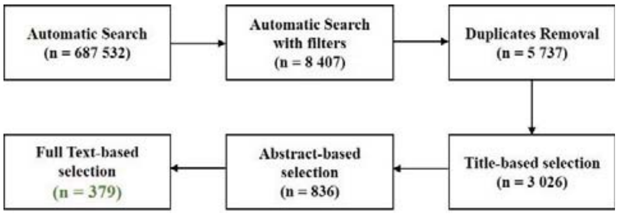


Fig. 1. Search and selection process

Phase 4. Title-based selection: In this phase, we first read each article's title to check whether the article was related to our study or not. Sometimes it was difficult to decide. In this case, the paper was included in the next phase. As a result, we ended up with 3 026 remaining papers.

Phase5. Abstract-based selection: We read and evaluated the remaining papers' abstracts against the exclusion and inclusion criteria to ensure they are related to our study. At the end of this step, 2 190 papers were discarded, and the remaining 836 papers, including any papers in doubt, were included in the next phase.

Phase6. Full-Text-based selection: We read the papers' full-text to define the final list of relevant studies. By applying inclusion-exclusion criteria, 457 out of the 836 papers have been excluded, resulting in 379 remaining articles.

TABLE II. SEARCH TERMS

Term	Synonyms
Personality	-
Prediction	Analysis - Analysing/ Analyzing Assessing - Assessment Classification - Classifying Computational - Computing Detecting - Detection Determining Estimation Extracting - Extraction Identification Inference - Inferring Perception Predict - Predicting Recognizing/ Recognising - Recognition

TABLE III. NUMBER OF STUDIES PER DATABASE WITH FILTERS

Database	Search results	Filters	Filtered search results
IEEE Xplore	1,638	Conferences Journals & Magazines Early Access Articles	1,628
Scopus	589,851	Limit to: Subject Area: Computer Science Document Type: Conference paper, Article, Article in press. Language: English	4,172
Web of science	96,043	Document Types: Proceedings Paper, Article Research Area: Computer Science Language: English	2,607

C. Data Extraction

To extract the data from the selected papers, we imported our library to Qiqqa research and reference manager, because of its ability to read and annotate pdfs. Then the data were extracted using an extraction form as depicted in TABLE IV and recorded in a Microsoft Excel Sheet. TABLE IV also includes the RQ to which each field contributes.

D. Data Synthesis

In order to present the findings of our study, we have used graphical visualizations (e.g. graphs and charts). The goal is to condense the major data for further analysis and to induce the conclusions.

III. Results

In this section, we address our RQs introduced in TABLE I. With this aim, we synthesize the data obtained from the extraction process described in II.C, and our results are as presented in the following sections.

A. RQ1. Demographic Characteristics

1) RQ1.1 When are the studies published?

To answer this question, Fig. 2 shows the distribution of primary studies according to their publication year. The first publication in this topic was in 2003, after a break of 2 years, other studies started to appear. From 2006 to 2009, the number of studies was about 3 each year. Starting from 2010 until 2018, the number of studies was significantly increasing, except in 2014. Finally, there are 10 papers in the first quarter of 2019. Even considering that this number is low, the interest in the area appears to have been growing over recent years.

2) RQ1.2 Where are the studies published?

Distribution per database:

We used in our research three main digital libraries: IEEE, Scopus and Web of Science. The distribution of the papers per these databases is as shown in Fig. 3. Scopus has the highest percentage of papers, followed by IEEE then WoS.

Distribution per publication type:

We have two publication types: Conference paper and Journal paper. The distribution of the 379 primary studies among these categories is shown in Fig. 4. According to our data, conference proceedings (with 60% of papers) are the most prevalent publication type.

Distribution per venue:

We have 229 different venues where the studies are published. Fig. 5 shows only journals that have published 3 papers or more. Lecture Notes in Computer Science, CEUR Workshop Proceedings, IEEE Transactions on Affective Computing and INTERSPEECH proceedings are the most concerned journals with the personality prediction topic.

3) RQ1.3 How publications are geographically distributed?

For answering this question, we considered the country to which belong the affiliation of the first author. In Fig. 6, we show the distribution of studies among the different continents. Asia (45%) and Europe (30%) are the most dominant continents.

TABLE IV. DATA EXTRACTION FORM

Category	Data item	RQ
Basic information	ID	
	Database	RQ1.2
	Title	
	Year	RQ1.1
	Venue	RQ1.2
	Publication type	RQ1.2
	Authors	
	1st author's affiliation (Organization and country)	RQ1.3
Approach characteristics	Personality Model	RQ2
	Input data type	RQ3.1
	Data source	RQ3.2
	Personality Prediction Category (APR/APP)	RQ4.1
	Prediction method	RQ4.2
	Method category	RQ4.3
	Feature type	RQ4.4

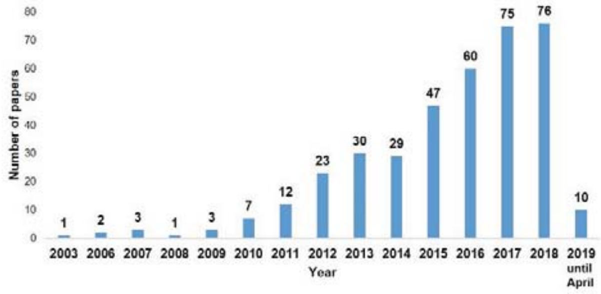


Fig. 2. Number of papers per year

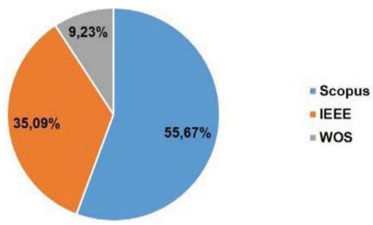


Fig. 3. Percentage of papers per database

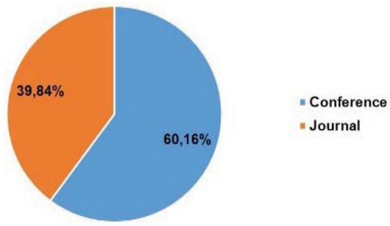


Fig. 4. Percentage of papers per publication type

Fig. 7 provides information about the percentage of studies published in each continent by year. It can be noticed that until 2012, studies were mainly published by institutions placed in Europe. Afterward, Asia takes the lead. Finally, in Fig. 8 we display how studies are geographically distributed among the different countries (only countries with 2 articles or more are visualized). China and the USA are by far the countries with more published studies (55 papers).

B. RQ2. Personality Models

By personality models, we are referring to different psychological categories of human personality. As shown in Fig. 9, the Big Five is by far the most used model in computing. Besides, we can remark that the Extraversion trait is getting a specific interest among different traits of personality.

C. RQ3. Input Data characteristics

1) RQ3.1 What types of data are used?

In Fig. 10, we display the different input data types used in our primary studies. We have 9 main categories: Text, Video, Speech, Logs (which include any kind of digital traces), Biometrics (such as face image, handwriting, signature, etc.), Profile (i.e. social media profile), Image, Interaction (e.g. mouse movement, touchscreen, eye gaze) and Physiological data (e.g. EEG signal, brain activity). Combination is when two or more main categories are used together. Finally, Other contains uncategorized data such as questionnaires, choices and preferences. As indicated in Fig. 10, Text is the most used input data type, followed by Video, then Speech.

2) RQ3.2 Which are the sources of data used?

From Fig. 11, we can see that almost half of the studies are using public corpuses dedicated to personality prediction. The others are creating their own dataset.

The most used public corpus are MyPersonality [20], The Speaker Personality Corpus (SPC) [21], PAN CLEF 2015 Corpus [22], Essays [23], The YouTube Personality Dataset [24], Youtube "First Impressions Challenge" Dataset [25] and others as illustrated in Fig. 12.

The specific corpus data, as shown in Fig. 13, are obtained from social media (e.g. Facebook, Twitter, Sina Weibo, etc.), Application (e.g. Games, websites, email, etc.), Devices (i.e. mobile phone or tablet), Human-robot interaction or other sources (such as recruiting people to record videos or write texts, etc.).

D. RQ4. Prediction characteristics

1) RQ4.1 Which category of personality prediction is used?

To answer this question, we looked at the used training data to find if the personality type is obtained from a self-assessment questionnaire or is attributed by other people. In the first case, it is an APR, which is by far the most treated as illustrated in Fig. 14, otherwise it is APP. Some studies are handling both cases, and others did not mention any information about that.

2) RQ4.2 What prediction methods are used?

For answering this question, we grouped the different methods by categories to make the visualization clear. The following is a description of each category included in Fig. 15:

- SVM: Support Vector Machines.
- Decision Tree Algorithms: it contains algorithms such as Random Forest, Decision Tree, Classification and Regression Tree, J48, etc.
- Neural Networks (NN): different neural networks are grouped in this category: Multilayer Perceptron, Convolutional NN, Long Short Term Memory NN, Deep learning, etc.

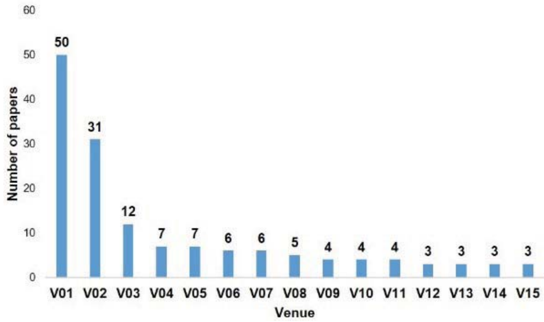


Fig. 5. Number of papers per venue

V01: Lecture Notes in Computer Science; **V02**: CEUR Workshop Proceedings; **V03**: IEEE Transactions on Affective Computing; **V04**: 13th Annual Conference of the International Speech Communication Association 2012, INTERSPEECH 2012; **V05**: Proceedings of the Annual Conference of the International Speech Communication Association, INTERSPEECH; **V06**: ACM International Conference Proceeding Series; **V07**: ICMI 2013 - Proceedings of the 2013 ACM International Conference on Multimodal Interaction; **V08**: WCPR 2014 - Proceedings of the 2014 Workshop on Computational Personality Recognition; **V09**: Communications in Computer and Information Science; **V10**: 2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops; **V11**: IEEE Access; **V12**: MM 2014 - Proceedings of the 2014 ACM Conference on Multimedia; **V13**: Advances in Intelligent Systems and Computing; **V14**: Conference on Human Factors in Computing Systems - Proceedings; **V15**: Eurasip Journal on Image and Video Processing

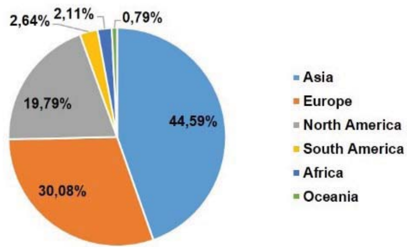


Fig. 6. Percentage of papers per continent

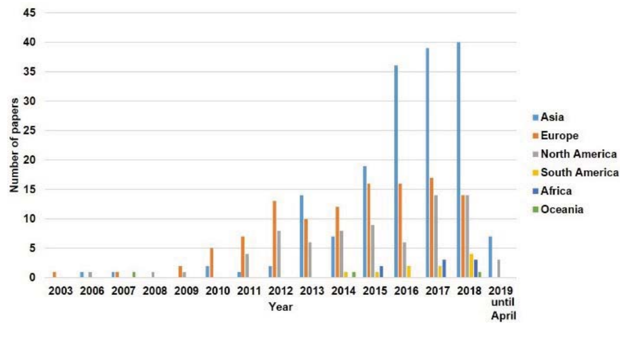


Fig. 7. Number of papers per continent and year

- Bayesian: it combines different variations of Bayesian Network and Naïve Bayes.
- kNN: k Nearest Neighbor algorithm.
- Linear Regression, Logistic Regression: they contain linear and logistic regression methods and their variations.

- Not ML: it contains equations and methods that are not following the machine learning approach.
- Rule-Based Algorithms: such as M5 Rules, ZeroR, OneR, etc.
- Ensemble Methods: it includes boosting, bagging and stacking algorithms.
- Regularization Algorithms: it has Ridge regression and Least Absolute Shrinkage and Selection Operator algorithms.
- Regression Methods: for example: Least Square, Ordinal Regression, Incremental Regression, Symbolic Regression, etc.
- Statistical Methods: it groups Hidden Markov Model, Gaussian Mixture Modelling, Conditional Random Fields, Maximum Entropy and others.
- Gaussian Processes.
- SMO: Sequential Minimal Optimization.
- Fuzzy Models: methods like Fuzzy Inference System and Fuzzy Logic and Reasoning.
- Clustering: e.g. K-Means algorithm, Affinity Propagation Clustering.
- Others: it groups algorithms that are used once and do not belong to any category above, as Reinforcement Learning and Transfer Learning.

Fig. 15 shows that SVM is the most used algorithm (used in 137 studies). Decision Tree and NN are nearly in the same position with 86 and 85 studies for each respectively. Then it comes the Bayesian with 73 papers. We should notice here, if we combine all the regression categories (Linear Regression, Logistic Regression and Regression Methods), this will result in a total of 77 papers, so that it exceeds the Bayesian class.

Fig. 16 illustrates the trends in using those methods per year. From 2009 to 2015, SVM has got a growing interest. In 2016, it still has the same attention, but interest in Decision Tree algorithms has suddenly escalated. The same occurs with NN algorithms in 2017 and 2018. Thus, NN is the last trend in personality prediction methods.

3) RQ4.3 What are the categories of the used methods?

Personality prediction is usually handled as a machine learning problem. As indicated in Fig. 17, 66% of the primary studies resolved the problem with classification techniques, 22% with regression methods and 4% with both of them. The remaining studies do not use machine learning.

4) RQ4.4 What are the types of features used for the prediction?

According to our data, there are 5 main categories of features: Textual, Visual, Audio, Behavioral and Physiological. Textual and behavioral features are the most used ones (33% and 21% respectively). Some papers combined 2 feature categories, which are referred by 'bi-modal' in Fig. 18. 'Multi-modal' used 3 or more classes.

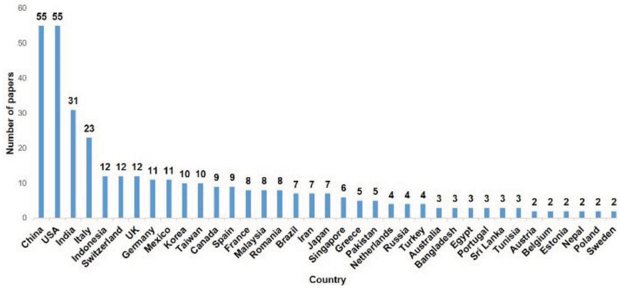


Fig. 8. Number of papers per country

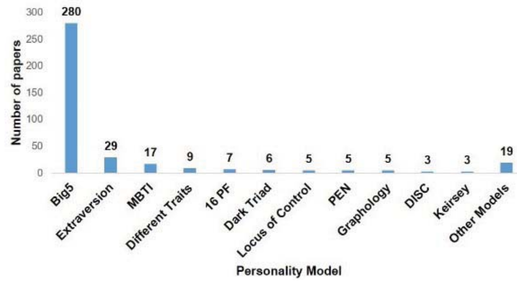


Fig. 9. Number of papers per personality model

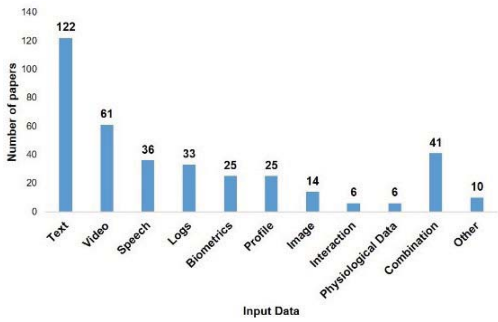


Fig. 10. Number of papers per input data

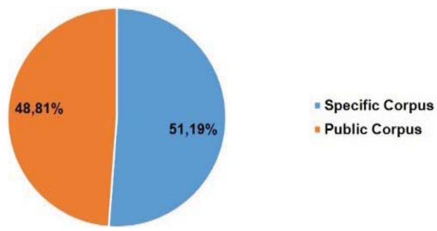


Fig. 11. Percentage of papers per data source

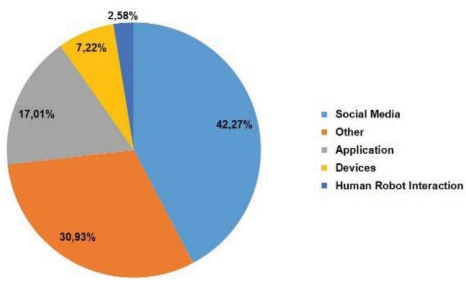


Fig. 12. Number of papers using each public corpus

IV. Discussion

We can observe from the results shown above that APPR is gaining an increased interest during the last years from the research community. However, given the fact that the majority of studies are conference papers, and mostly published in proceeding journals or general computer science interest journals, this domain still needs time to become a mature and independent research field.

Geographically, China and the USA are the countries that invest the most in this topic. As these states are major economic power, we can assume that this interest is due to a big potential expected from APPR and its applications.

The psychological side of APPR is about choosing the personality model. All the models used in those studies are inspired by the trait theory. The latter represents personality in terms of numerical values, which is convenient for computer processing. More precisely, Big Five is the most used model. On one hand, it is widely accepted in the psychological community [2]. On the other hand, this model describes the essential traits of personality, without being too limited in scope (like Eysenck's model with three traits) or too complicated (like Cattell's model with 16 dimensions), which make the prediction task more affordable.

The technical side of APPR includes the input data, prediction methods and features. Among different data inputs, researchers worked the most with text data retrieved from sources like social media, blogs, etc. Text is widespread through the internet, and it is easy to collect to construct a dataset. the other input types are more difficult to deal with, and sometimes require an experiment setting and recruiting people to participate. Moreover, the recognition of personality traits from text is now an established computational task [26], [27].

As compared to APP, APR is more largely studied. Researchers are more concerned with the true personality of individuals, but how others perceive theirs' is also important and can be useful in different applications. Therefore, APP is a fresh field to explore.

The trend in the last 5 years concerning prediction methods is the use of SVM and recently NN. The choice of SVM can be justified as it is an efficient algorithm in high dimensional spaces and more suitable for small datasets [28], which are the characteristics of many studies. As for NN, it makes sense to try it in this case as well, as it has achieved a big success in different computing issues. APPR is widely resolved as a classification problem rather than regression. In the first approach, the results are in terms of discrete class labels for every trait (e.g. high or low). This representation is more likely to be understandable and interpretable by normal individuals. Otherwise, the regression

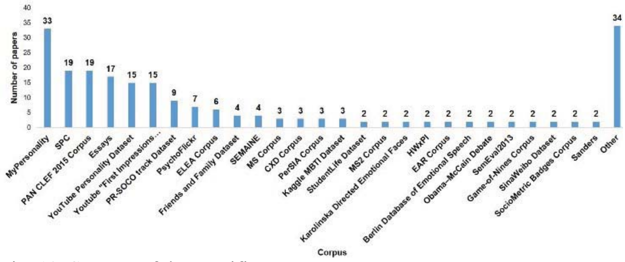


Fig. 13. Sources of the specific corpus

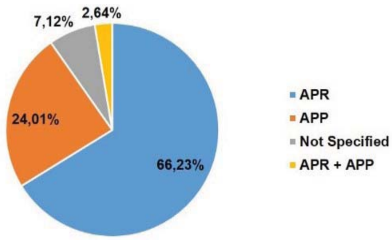


Fig. 14. Percentage of papers per prediction type

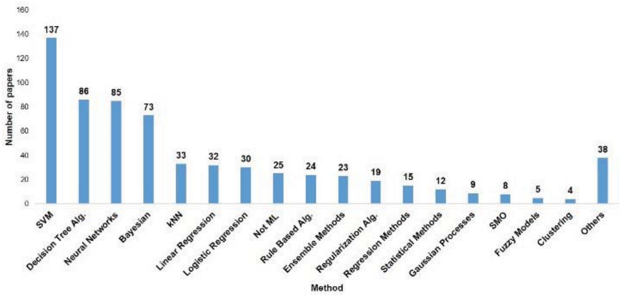
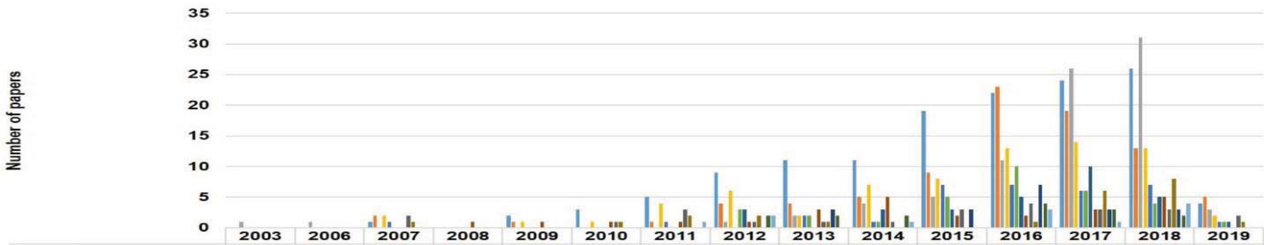


Fig. 15. Number of papers per method



	2003	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
SVM			1		2	3	5	9	11	11	19	22	24	26	4
Decision Tree Alg.			2		1		1	4	4	5	9	23	19	13	5
Neural Networks	1	1						1	2	4	5	11	26	31	3
Bayesian			2		1	1	4	6	2	7	8	13	14	13	2
kNN			1				1		2	1	7	7	6	7	1
Linear Regression								3	2	1	5	10	6	4	1
Logistic Regression								3		3	3	5	10	5	1
Not ML				1	1	1	1	1	3	5	2	2	3	5	
Rule Based Alg.			2			1	3	1	1	1	3	4	3	3	2
Ensemble Methods			1			1	2	2	1			1	6	8	1
Regularization Alg.									3		3	7	3	3	
Regression Methods								2	2	2		4	3	2	
Statistical Methods							1	2		1		3	1	4	

Fig. 16. Number of papers per method and year

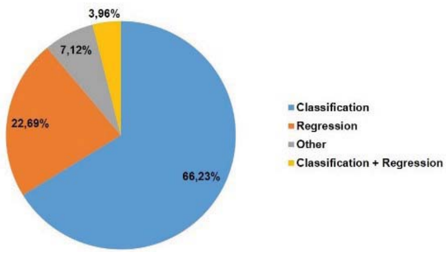


Fig. 17. Percentage of papers per method category

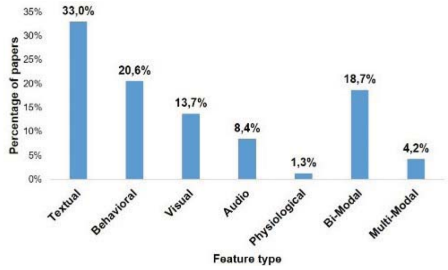


Fig. 18. Percentage of papers per feature type

gives a score for each trait (a continuous value) which means that the results are more detailed and specific.

Finally, for the used features, we can extract only textual features (e.g. linguistic or psycholinguistic characteristics, etc.) from text data, while from video data, we can obtain visual or/and textual or/and acoustic features, as well with speech input (without visual features).

To conclude, the research field of APPR is widely explored. However, in order for it to gain trust and be implemented in real-life applications and systems, accuracy should increase to high levels. To reach that, more studies should be conducted, with different approaches, methods and consistent data.

V. Conclusion

With the goal to present a comprehensive overview of the state of the art in APPR, we conducted an SMS following recognized guidelines. Applying a rigorous protocol, we found 8407 papers that we reduced to 379 after several steps. Using the information extracted from those studies, we could identify the growth pattern of this topic, journals interested in it and countries investing the most in researches in this field. Moreover, we detected what were the most used prediction methods, features, inputs, data sources, alongside APPR categories and personality models.

We believe that this work can help researchers to identify opportunities and possibilities for new studies. It may be helpful to provide a comparison between different approaches in terms of methods and accuracies. However, we could not do it in this work, as our research is of a large scope. Therefore, it is preferable to consider this in a separate work, such as a systematic review, with a specific and limited research scope.

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