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COMPUTATIONAL MODELS AND DATASETS IN PERSONALITY PREDICTION – A SYSTEMATIC LITERATURE REVIEW

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Abstract. *The study of personality is gaining attention in the most recent years. Personality prediction is found to be potentially beneficial for the development of recommender systems and alternatives for traditional personality assessments. Moreover, with the growth of numerous social media platforms, these platforms are a potential gold mine to train intelligent personality prediction systems. This systematic literature review aims to explain the impact of social media in personality prediction dataset choice, and the most optimal models for personality prediction systems. The study concludes that social media has a large impact on dataset choice, with 17 out of 19 observed publications utilizing social media as their source of dataset. The state-of-the-art models were dominated with boosting and attention-based deep learning models such as BERT, ULMFiT, AttRCNN, and XGBoost.*

Keywords: Personality prediction, Social media, Machine learning, Deep learning

1. **Introduction.** The era of information has led to many breakthroughs to diverse fields of study, including the study of personality. Personality is the study of behavioral character of a person [1]. Its study is advantageous to various fields, as it is found to relate with an individual's working performance [2], the study of companion agents [1], and recommender systems [3]. In studying personality, there exist multiple measurement methods for the intangible element.

Personality is represented with various metric models, with some well-known to the field of machine learning such as the Five Factor Model (also named as Big Five or FFM), Myers-Briggs Type Indicator (MBTI), and DISC model. The FFM model [4] consists of five personality traits, which are *Openness*, *Conscientiousness*, *Extraversion*, *Agreeableness*, *Neuroticism*. Every trait in the FFM model has its own intensity value, therefore different individuals have different values for these five traits. This is similarly true for the DISC model [5], as it stands for *Dominance*, *Influence*, *Steadiness*, and *Conscientiousness*. The MBTI model, however, works differently compared to its two counterparts. The MBTI model categorizes individuals into sixteen different characters of personality, defined by combinations of four traits [6]. These traits consist of *Extroverted/Introverted*, *Sensing/Intuitive*, *Thinking/Feeling*, and *Judging/Perceiving*. An individual with traits of being an extroverted, sensing, thinking, and judging person is defined as an *ESTJ* individual.

The benefits of studying personality and its diversity of metrics provide a purpose to the promising study of personality prediction. Rather than traditionally assessing an individual with a psychological assessor, an automated personality prediction may serve as a cheaper alternative or complementary data for concerned parties. As a result, numerous

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studies focused on developing a personality prediction system from text. Considering the amount of text required to train the system, some of the datasets for the aforementioned systems are mined from social media platforms.

Social media plays an undeniably important role in the exchange of textual information. It is found to be used for sharing news [7], fundraising [8], and sales [9]. Additionally, social media is a host to a humongous amount of data. Twitter (https://twitter.com/) for example, owns 331 million of active users in early 2019 [10]. This serves as a potential gold mine for text-based datasets and the development of Natural Language Processing (NLP).

Knowing the possibility and potential of personality prediction, this Systematic Literature Review (SLR) aims to analyze the influence of social media in building text-based personality datasets for machine learning and the developments of the current state-of-the-art personality prediction models. This SLR implements the PRISMA methodology to review publications from multiple sources (Google Scholar, Arxiv, and ACL Anthology). The publications will be searched with predefined queries to obtain the initial pool of eligible documents. Then, these publications are further screened by their publication year and content suitability. Finally, 19 publications which passed the screening criteria are reviewed thoroughly to answer predefined research questions. At the end of the study, we conclude the challenges of personality prediction obtained from the review to contribute in its future development.

2. **Methods.** This systematic literature review is performed to provide a comprehensive analysis in answering the research questions. The research questions in this SLR are described as:

- RQ1 – What are the datasets to be used in personality prediction from text?
- RQ2 – What are the most optimal models for personality prediction from text?

In answering the aforementioned research questions, this SLR adopts PRISMA [11] (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) as its framework. The flowchart of the PRISMA methodology performed in this SLR is described in Figure 1.

The documents for this SLR are initially identified with multiple searches on online platforms and libraries such as Google Scholar (https://scholar.google.com/), Arxiv (https://arxiv.org/), and ACL Anthology (https://www.aclweb.org/anthology/). Some of these platforms support logical operators such as *AND* and *OR* to manipulate the search. The queries used for the search process are enlisted as:

- personality prediction text
- personality text
- personality prediction
- personality recognition
- personality prediction *OR* personality classification *OR* personality recognition *OR* predicting personality *OR* recognizing personality *OR* classifying personality

Upon obtaining the initial records, time filtering is performed. Documents which are older than 2015 are disposed from the search pool to ensure the freshness of the gathered information. Then, documents of unrelated field of study and personality prediction from text is excluded from the search pool. A document is deemed related to this study if its full text or abstract emphasizes model development for text-based personality prediction. The rest of the documents are chosen as the information resource of this SLR. The detailed number of documents gathered from each online library and platform is defined in Table 1. Quantities which are unknown due to lack of search results information from the libraries are written as undefined.

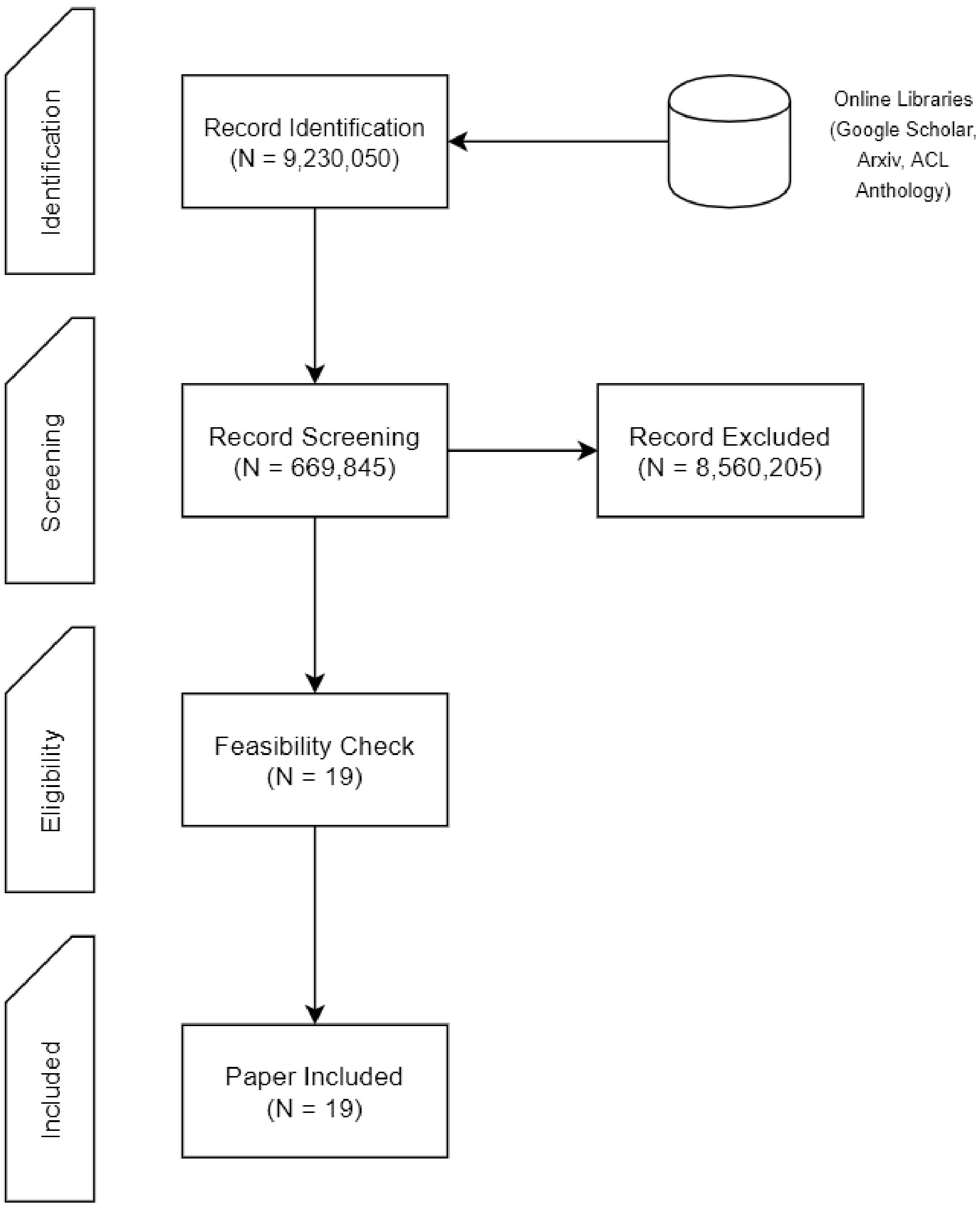

Figure 1. PRISMA flowchart

Table 1. Record selection

Source	Found	Screened	Selected
Google Scholar	9,230,000	669,800	12
Arxiv	50	45	4
ACL Anthology	undefined	undefined	3

3. Result.

3.1. List of paper publications. There are 19 publications to be included in this SLR. The chosen publications are found in Table 2.

3.2. List of individual studies. After the record collecting phase, relevant data is extracted to answer the predetermined research questions. The data to be extracted includes the model and dataset for the proposed system and its performance. Then, a thorough analysis is performed to answer the research questions.

Table 2. Chosen publications

Source	Year	Title
ACL Anthology	2018	Modeling Personality Traits of Filipino Twitter Users
ACL Anthology	2018	Reddit: A Gold Mine for Personality Prediction
ACL Anthology	2019	Incorporating Textual Information on User Behavior for Personality Prediction
Arxiv	2017	Lexical-Semantic Resources: Yet Powerful Resources for Automatic Personality Classification
Arxiv	2019	Automatic Extraction of Personality from Text: Challenges and Opportunities
Arxiv	2019	Automatic Text-Based Personality Recognition on Monologues and Multiparty Dialogues Using Attentive Networks and Contextual Embeddings
Arxiv	2019	Myers-Briggs Personality Classification and Personality-Specific Language Generation Using Pre-Trained Language Models
Google Scholar	2015	Personality Classification Based on Twitter Text Using Naive Bayes, KNN and SVM
Google Scholar	2015	Personality Traits on Twitter-or-How to Get 1,500 Personality Tests in a Week
Google Scholar	2015	Predicting Personality Traits of Chinese Users Based on Facebook Wall Posts
Google Scholar	2016	A Language-Independent and Compositional Model for Personality Trait Recognition from Short Texts
Google Scholar	2016	Automatic Personality Recognition of Authors Using Big Five Factor Model
Google Scholar	2016	Personality Estimation from Japanese Text
Google Scholar	2016	Predicting Personality from Social Media Text
Google Scholar	2017	Deep Learning Based Personality Recognition from Facebook Status Updates
Google Scholar	2017	Deep Learning-Based Document Modeling for Personality Detection from Text
Google Scholar	2017	Personality Prediction Based on Twitter Information in Bahasa Indonesia
Google Scholar	2017	Personality Prediction System from Facebook Users
Google Scholar	2018	Deep Learning-Based Personality Recognition from Text Posts of Online Social Networks

Table 3. Dataset source summary

Dataset	Count	Publications
Facebook	8	[12, 13, 14, 15, 16, 17, 18, 19]
Twitter	7	[16, 20, 21, 22, 23, 24, 25]
Forums	2	[26, 27]
Non-Social Media	2	[28, 29]
Reddit	1	[30]

3.2.1. *What are the datasets to be used in personality prediction from text?* The different sources of dataset for the observed personality prediction studies may be viewed in Table 3. Compared to the other sources, Facebook is the most chosen dataset source with a number of 8 publications. This is mostly due to the popularity of the MyPersonality dataset which was created by Celli et al. in 2013 [31]. The dataset contained 9900 status updates from 250 users, labelled with FFM values accordingly. Unfortunately, the dataset is no longer supported since April 2018 from its authors (https://sites.google.com/michalkosinski.com/mypersonality).

According to the summary in Table 3, 17 out of 19 publications chose social media for the dataset of their personality prediction system. This concludes that the impact of social media to this field of study is great, with 89% of the observed studies using social media datasets.

3.2.2. *What are the most optimal models for personality prediction from text?* A summary of model utilization in the observed publications may be seen in Table 4. Among all of the other models, the SVM (Support Vector Machine) [32] model is the most used as comparison in these studies. This is likely due to the popularity of SVM models as a classification or regression (Support Vector Regression) tool. The usage of SVM is found more frequently in the publications of year 2015, compared to deep learning models such as CNN (Convolutional Neural Network) [33] and MLP (Multi-Layer Perceptron) [34].

TABLE 4. Model utilization summary

Model	Count	Publications
SVM	10	[12, 13, 14, 18, 20, 21, 25, 26, 29, 30]
CNN	5	[17, 18, 19, 28, 29]
MLP	4	[17, 18, 29, 30]
Logistic Regression	3	[18, 20, 22]
BERT	2	[27, 28]
Linear Regression	2	[20, 24]
LSTM	2	[18, 28]
RNN	2	[17, 23]
GRU	1	[18]
Parse Tree + SMO	1	[15]
RCNN	1	[19]
Receptiviti API	1	[16]
ULMFiT	1	[26]
XGBoost	1	[25]

Interestingly, deep learning models are used only since the year 2016 with the development of Bidirectional RNN (Recurrent Neural Network) in C2W2SPT (Character to Word to Sentence for Personality Trait) model [23]. The RNN-based C2W2SPT model was tested on Twitter dataset which achieved 0.109 RMSE on the conscientiousness trait. Aside from RNN-based models, deep learning models are more frequently found in 2017 such as CNN, MLP, LSTM (Long Short-Term Memory) [35], and GRU (Gated Recurrent Unit) [36]. Boosting algorithm such as XGBoost is also implemented for personality prediction in 2017, achieving an astounding 97.99% accuracy on Indonesian Twitter dataset [25]. It was not until 2018 that attention mechanism is introduced for personality with a model named AttRCNN [19].

Soon after, pre-trained language models and transformers herald the breakthrough of transfer learning in NLP as they were also implemented in personality prediction from text. The transformer architecture is originally introduced in 2017 as encoder-decoder models with self-attention [37]. After the introduction of transformers, the development of BERT [38] is introduced, which then enables researchers to utilize the pre-trained weights and fine-tune them to the study requirements. BERT is used in personality prediction on PersonalityCafe MBTI dataset [27], which achieved 0.7583 accuracy for one of the traits.

Transfer learning is also found to work on LSTM-based language models such as ULMFiT (Universal Language Model Fine Tuning) [39]. The ULMFiT model is capable of achieving state-of-the-art performance on small datasets. Additionally it performs well on multilingual datasets. In a study by Akrami et al. [26], ULMFiT is used on a Swedish dataset which successfully achieved 0.82 average FFM classification accuracy.

Even though the SVM model has the highest utilization frequency, it does not possess the best overall performance on these studies. A study by Majumder et al. has proven that the SVM model is inferior to a CNN deep learning model [29]. It is found in that study that CNN-based model with multilayer perceptrons classifier could achieve up to 62.68% accuracy, which is not possible on SVM models. Another similar study has also proven that XGBoost triumphs in the performance race of personality prediction, compared to SVM models [25]. Their SVM-based model achieved 76.23% average accuracy which is significantly outperformed by the XGBoost model which achieved 97.9962% accuracy.

Considering the different datasets and performance metrics utilized in the publications, the best performing model is still unclear. However, most of the recent models utilized deep learning and boosting models such as XGBoost which achieved a significant performance compared to the other traditional machine learning models.

4. **Future Challenges.** There are several challenges to face in the study of personality prediction. One of them is the availability of datasets with non-English languages. Most personality datasets consist of English texts, which is not suitable for studies focusing on other languages. These studies must focus on the process of data gathering in addition to developing the personality prediction model. An example is the study of personality prediction on Swedish text by Akrami et al. [26] which needed to cover the entire data gathering and labelling process before implementing it with ULMFiT model.

Aside from language barrier, the diversity of datasets and personality metrics also serve as a potential challenge to personality prediction. Previous studies have used varying datasets and personality metrics (such as FFM and MBTI) to train their proposed models. This complicates the process of performance comparison between state-of-the-art models which might lead to the use of unsuitable model in studies. Future studies should consider to compare the most recent state-of-the-arts with suitable datasets and metrics to obtain a clear comparison of performance between these models.

5. **Conclusion.** Recent trend of text-based personality prediction has been analyzed in this study. A total of 19 publications have been observed thoroughly in this systematic literature review to analyze the most optimal models for personality prediction and the effects of social media in their dataset choice. It may be concluded that social media has a relatively large impact on text-based dataset usage, especially in the personality prediction field of study. 17 out of 19 publications observed in this study are found to utilize the datasets originating from social media.

Aside from the dataset trends, numerous machine learning models were also implemented in these publications. SVM is found to be the most used model in personality prediction studies, but does not necessarily achieve the best performance compared to the other models. A conclusion of the best performing model can hardly be inferred due to the different choice of performance metrics and datasets. The state-of-the-art models of personality prediction are composed of mostly attention-based deep learning models (AttRCNN, ULMFiT, BERT, etc.) and boosting models such as XGBoost.

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