

## Personality Measurement Design for Ontology Based Platform using Social Media Text

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### ABSTRACT

Human behavior quantification is an essential part of psychological science. One of the cases is measuring human personality. Social media provide rich text, which can be beneficial as a data source to get valuable insight. Previous researches show that social media offered favorable circumstances for psychological researchers by tracking, analyzing, and predicting human character. In this research, we propose a personality measurement design to help to assess human character through linguistic usage from human digital traces. We construct our model by classifying social media text to the pre-determined personality facet from Big Five personality traits, mapping the knowledge to the ontology model, and implementing the model as a platform dictionary. Our model is based on the Indonesian language, which to the best of our knowledge is the first in the subject area. The platform is running effectively by using a well-established sorting algorithm, called the radix tree. Our objective is to support psychological science in adapting to a new technological era.

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## 1. Introduction

The presence of advanced technologies, such as social media platforms and mobile devices, are shifting the way on how people communicate. Social media users have the freedom to upload daily routine information, exchanging messages, or even basic conversations [1]. The content created by the users is formed into digital traces. The personality of users revealed through their writing or textual content [2]. Each personality has its own charm that deserves attention over its complex arrangement. There are thoughts, hearts, and feelings that can change over time [3]. Hence, measuring human personality is a hard problem regarding the dynamic feeling's alteration.

Personality measurement has become the most extensive research in the field of Psychology [4]. The legacy methodology of personality assessment performed by interview and written examination [5]. Those methods are integrated method, where an interview is conducted to validate the test result. The characteristic of legacy methodology requires fulfillment instruments, such as the physical tools and psychologists. In order to adapt to the new technological era, some alternative methodologies are developed for bringing a faster process and result. One of them is the measurement through its natural environment or using digital traces on social media [6]. In this research, we utilize digital traces to put forward an automation personality measurement for minimizing fulfill instruments in the legacy methodology. Thus, it

would significantly reduce the cost and reduce the time process of getting the results. This approach needs to be developed, considering that automation is the most demanded characteristic of the Industry 4.0 era.

According to Madden et al. [7], digital traces, which consist of user information, e.g., personal information, shared texts, pictures, and videos, are a proof dataset that cannot be ignored, which expressed online human activity. These footprints are offered valuable opportunities for psychology research in understanding human characteristics [8]. Previous researches have assessed human personality through social media, such as Bhardwaj et al. [9], who assess personality through Facebook and LinkedIn and Park et al. [6] who applying the regression model to predict human character based on social media language.

Most of the research generally uses a machine learning approach, in contrast to our study, which utilizing the ontology approach. Machine learning provides us some leverage, such as the speed of analysis regarding large-scale data [10]. It is also able to predict personality on various forms of data like text, speech, and image [11]. However, the machine learning approach has some weaknesses in processing each meaning and intention of words due to language uniqueness [12]. Ontology afford us a better understanding of contextual knowledge [13]. There is an opportunity to use ontology as a basis for measuring human personality through the words on linguistic usage. Thus, in terms of measuring human nature through social media textual data, the

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ontology model provides a more accurate result than a machine learning approach as long as the collection word type in the ontology model's corpus is prosperous. The following approach scheme is shown in Fig. 1.

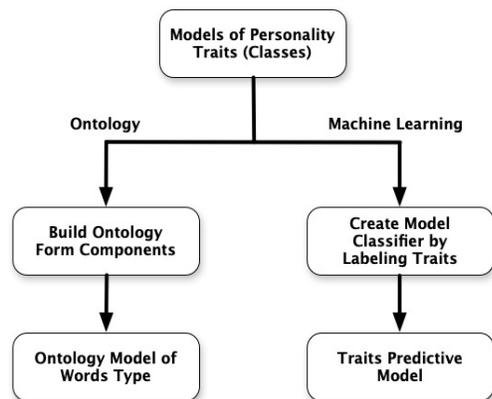


Figure 1: Personality Traits Model Scheme between Ontology and Machine Learning Approach

Fig. 1 shows the difference between ontology and machine learning model schemes. On the ontology model scheme, the personality trait model established by mapping words that reflect personality as a model's forming component. Those collections of words then verified by experts and utilized as a dictionary for measuring personality. This model is a representation of an expert's knowledge and adequate to map more than one personality trait in the complex sentence. Meanwhile, the personality trait model on the machine learning model scheme is a depiction of a machine's algorithm according to the labeling process. The machine interprets the label on the training dataset as a rule for predicting personality. Therefore, the approach of the machine learning model scheme is entirely different than ontology. The ontology model scheme is only mapping the words with reference to an expert's knowledge, while machine learning is predicting based on the learning result of the machine.

To the best of our knowledge, research of personality measurement has put forward in several personality traits taxonomies based on specified purposes, such as for assessing job placement and natural human emotion. In this research, we want to use the most general taxonomy of human's essential persona. The Big Five Personality theory gets a consensus of a general taxonomy regarding human personality traits [14]. It also able to represent and simplify the diverse characteristics of a human's personality [15]. The Big Five Personality Traits is built by examining several unique human attributes in their linguistic usage. This theory also offers prized terms called Revised Neuroticism-Extraversion-Openness Personality Inventory (NEO-PI-R) metric, which facilitate the exposure psychological characteristic of broad trait [16]. In this research, we use the Big Five Personality Traits Theory with the NEO-PI-R metric as a domain knowledge of our ontology model. The personality divided into five domains and further divided to thirty facet scales. Our research also applies the lexical hypothesis as a basis for analyzing textual content in social media. Based on research of Raad and Mlacic [17], the lexical hypothesis is a process of understanding the meaning of textual data. The lexical hypothesis is qualified to map the personality traits through words in a language [18].

In terms of model development, the needs of an open-source platform are essential. The advantage of creating the platform are model crowdsourcing, public corpus enrichment, correction, and verification. Hence, the platform is significantly enhancing the model's value over time. Nowadays, a platform with an ontology-based model for measuring human personality is still rare. In favor of getting a better model for measuring personality, we implement the model into a platform. This research aim is to show the way on how we develop a design in mapping human character by utilizing the ontology model. The model constructed by a collection of words that refer to personality in Bahasa. Our study mapped 2,331 instances in different facets and traits — those instances used as the corpus in our platform.

## 2. Literature Review

This chapter provides theoretical foundations related to the personality measurement proposed model based on the ontology approach. Literature review is sorted according to the data flow from social media data collection, personality definition, the personality traits, the ontology as the knowledge representation literature, and at last, is the radix tree algorithm used to parse and sort social media texts.

### 2.1. User-Generated Content

According to Naab and Sehl [19], user-generated content (UGC) has three criteria, there are 1). UGC is characterized by a rate of personal contribution, 2). UGC must be disclosed, and 3). UGC is built outside the sphere of occupation and professional routines. Besides, Wyrwoll stated that user-generated content is a content that is published online via various platforms by its user [20]. The users are not only the person but also the organizations. The substance classified as a UGC has similar characteristics, such as publicly accessible to other users, need a creative effort to create, and not a result of expertise routines and practices. UGC also defined in many forms, like blogs, posts, chat, podcasts, images, videos, tweets, and many other ways. In this modern era, UGC is a substantial information source for discovering knowledge from human digital activities [21]. Existing studies reveal that there is a high correlation between personality and personal inclination [22]. UGC indirectly shows beneficial information, like the user's demand, lifestyle, and personality. Hence, we utilize UGC in social media to measure human personality.

### 2.2. Personality

Personality is defined as a set of a person's characteristics, including acting, thinking, and feeling. Personality also correlates with emotions, values, attitudes, and talents [23, 24]. These attributes are establishing a unique persona of an individual and differentiate one person from another [25]. According to Stemmler, a person's personality closely related to language usage in speaking or writing [2]. Language is the most prevalent and reliable tool for people to convey their internal thoughts and emotions in giving comprehension to others [26, 27]. Hence, the linguistic usage of a person is an essential subject in the field of psychology and communication.

Previous research has examined human personality through linguistic usage. Howlader et al. predict Facebook user's personality through status and linguistic features by applying

regression models [28]. Boyd and Pennebaker propose a complementary model that provides big data solutions to measure human personality based on words people use [29]. Pietro et al. and Bogolyubova et al. [30, 31] who discovered the dark triad personality of social media users their online communication. Flekova and Gurevych [32] predict the personality of fictional characters in the novel using lexical-semantic features. Another research is Wei et al. [33], who predict human personality via information in digital traces and conversation logs.

2.3. Big Five personality Traits

Big Five Personality Traits is a model that identifies five characteristics of personality. It is also recognized as the OCEAN model, which stands for Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism (OCEAN) [34, 35]. This model is related to the lexical hypothesis and stated that language in daily interactions is a reflection of the most personality characteristics [36]. Thus, the Big Five Personality Traits predict and describe essential personality differences. In favor of getting a clearer explanation, Rossberger in [37] describes five traits below:

Table 1: Big Five Personality Traits

Big Five Personality Traits	Definition
Openness	or usually called openness to experience: extent to which individuals exhibit intellectual curiosity, self-awareness, and individualism/nonconformance.
Conscientiousness	extent to which individuals value planning, acquire the tenacity quality, and achievement oriented.
Extraversion	extent to which individuals involved with the external world, encounter enthusiasm and other positive emotions.
Agreeableness	extent to which individuals' value mutual effort and social harmony, modesty, dignity, and trustworthiness.
Neuroticism	extent to which individuals deal with negative feelings and their propensity to emotionally overreact.

According to Costa and McCrae's study [16], NEO-PI-R was advanced in samples of middle-age and older adults. The NEO-PI-R included scales to measure six conceptually derived facets in each OCEAN. The scales show generous internal consistency, temporal cohesion, convergent and discriminant validity against partners and peer ratings. Table. 2 shows the six facets which explaining each of the factors in personality traits.

2.4. Ontology and Knowledge Representation

Ontology is a collection of concepts which able to model terms of vocabulary into a domain knowledge [38]. From the perspective of computational science, ontology is explained as a concept to model the system structure. For example, the relevant entities and relationships that exist from observations are useful for specific purposes [39].

Table 2: NEO-PI-R Metric

Personality Traits	Facet	Description
Openness	Aesthetics	Artistic interests; believe in the value of art/do not love poetry
	Fantasy	Imagination; have an expressive imagination/seldom daydream
	Actions	Adventurousness; prefer variety /dislike changes
	Ideas	Intellect; admire convoluted problems/avert discussion
	Feelings	Emotionality; encounter emotions intensely/rarely get emotional
	Values	Liberalism; tend to elect for liberals/believe in one true divinity
Conscientiousness	Competence	Self-efficacy; accomplish tasks successfully/misunderstand the situation
	Order	Orderliness; prefer to order/abandon a mess
	Dutifulness	Follow the rules/break the rules
	Achievement-Striving	Work hard/just do the task
	Self-Discipline	Get task done right away/waste the time
	Deliberation	Cautiousness; avoid error carefully/charge into things directly
Extraversion	Warmth	Friendliness; make friends effortlessly/hard to make friends
	Gregariousness	Love large parties/prefer to be alone
	Assertiveness	Take action/wait for others to get the way
	Activity-Level	Regularly busy/love to take it easy
	Excitement-seeking	Love excitement/dislike loud music
	Positive Emotions	Cheerfulness; radiate joy/am seldom amused
Agreeableness	Trust	Trust others/distrust people
	Compliance	Morality; never deceive/use false praise
	Altruism	Make people feel pleasant/despise on others

Personality Traits	Facet	Description
	Straightforwardness	Cooperation; easy to fascinate/have a sharp tongue
	Modesty	Dislike being center of attention/think highly of myself
	Tender-mindedness	Sympathy; sympathize with the destitute/believe in people
Neuroticism	Anxiety	Worry about things/relaxed most of the time
	Angry-Hostility	Get enraged easily/rarely get annoyed
	Depression	Often feel miserable/feel satisfying
	Self-Consciousness	Easily frightened/not being intimidated easily
	Impulsiveness	Immoderation; often be affected by other/easily resist temptations
	Vulnerability	Panic easily/remain calm under pressure

Ontology associated with discovering and modeling reality under particular perspectives [40]. It focused on the structure and nature of an object [41]. Ontology also pointed out to a representational knowledge which indicates the type of class or entity associated with the relationship of the subtype [42].

Ontology generally has fundamental form components, i.e., class, instance, and relation [43]. Class is referring to a set of multiple instances, like words and phrases. An instance is a scope that considered in the ontology domain knowledge. A relation is defined as a relation among classes or instances [44]. This method is flexible, easy to modify, understood by humans and machines, and able to integrate with machine learning. Ontology has at least four evaluation methods [45]: 1). The Golden Standard; 2). The Application-based; 3). The Human Assessment; 4). The Data-Driven. Our study needs validation and evaluation for each instance in the model before implementing it on the platform.

Recent research has shown that ontology is able to represent knowledge for measuring personality. Some of the studies are that applying linguistic feature analysis and ontology model to measure human nature through social media data [46]. Another research computes human personality derivation in the modern physiognomy domain [47]. [48] also shows that ontology is a representative way to measure contextual knowledge, by building a complex domain of music and see how it relates to the domain of personality. A few research examples were clarifying how ontology might contribute to the analysis, comprehension, and research about human behavior and psychological research. Most of these existed researches are mainly focused in the English language, in contrast to our research which concerns in Bahasa.

### 2.5. Radix Tree

The dictionary which consists of strings data type is very-time consuming. A sorting algorithm is needed in order to get a more efficient process. Radix Tree is one of several algorithms that able to sort data in a database. Radix tree also beneficial for constructing associative arrays that expressed through the keyword in the form of strings. According to Mauro, radix tree is worked by labeling edges with a sequence of strings rather than characters, and constricting chains of nodes into a single element. Hence, radix tree is running more efficiently compared to a regular tree [49]. The instance of radix tree displayed in Fig. 2.

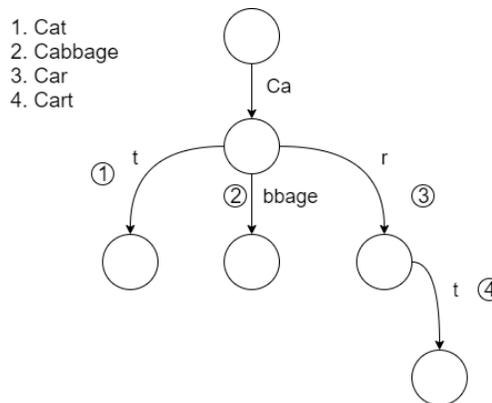


Figure 2: The Instance of Radix Tree Algorithm

### 3. Methodology

Our idea is to collect social media posts of people who considered influential in society. Their posts most likely to be responded by the public, which will generate conversations, and often set standard for informal language in Bahasa. In the model construction, we map words and phrases to a certain personality, which will validate by experts. There are several steps to construct the proposed model. Those steps are data collection, data preparation, model construction, model validation, platform construction, and conclusion. The research workflow is shown in Fig. 3. In contemplation of earning comprehensive understanding, we also illustrate the conception of our research methodology in Fig. 4.

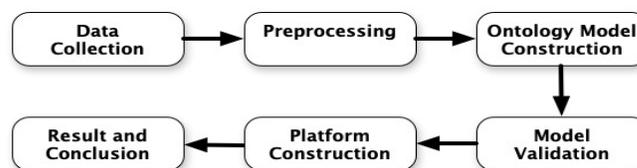


Figure 3: The Proposed Model Workflow

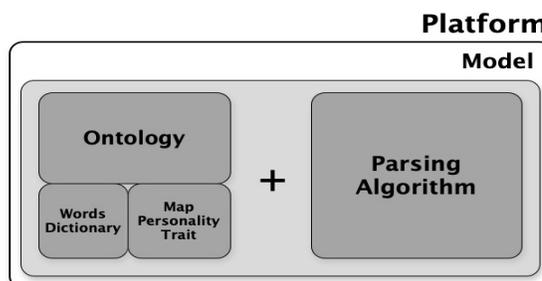


Figure 4: The Conception of Research Methodology

### 3.1. Data Collection

Our research utilizes real-world conversations on *Twitter* social media. A recent study shows that *Twitter* provides a valuable chance to study human behavior in a natural environment [1]. In the data retrieval process, we use three samples i.e., the famous user in *Twitter* social media with specific criteria. Our samples criteria are:

1. Verified accounts or having tweets with more than 1000 tweets or 500,000 followers.
2. Shows the latest activity with different tweets.
3. Shows many interactions with other accounts.
4. Not a protected account.

Based on those criteria, we have collected 13,047 tweets from three selected users. We comprehend that despite having the same principles in data collection, this collection of famous people who have different character tendencies, and this is the reason why we conduct this research.

### 3.2. Preprocessing

The data preprocessing is required to clear irrelevant data, such as URLs, symbols, and other terms, which is not beneficial for this research [50]. This process objective is to get substantial information over the data [51]. According to Khadim, preprocessing is a process of improving data quality while reducing barriers that will occur in the classification process [52]. The preprocessing is divided into several steps shown in Table. 3.

Table 3: Preprocessing Steps

Steps	Name of Preprocessing Steps	Definition
1	Case Folding	Transforming all capital letters to lowercase letters.
2	URLs Removal	Eliminating web page links
3	Symbol and Number Removal	Delete the symbol and number in the document
4	Tokenizing	Splitting the sentences into a token
5	Phrases Lookup	Check if there are any phrases in the token
6	Synonym Recognition	Determine the synonym of a word and replace it based on a dictionary
7.	Word Generalization	Replacing a word into a more general word in order to reduce data redundancy

### 3.3. Ontology Model Construction

This model is established by classifying words in each tweet into thirty classes in the NEO-PI-R metrics and afterward generalize it into Big Five Personality traits. Those collections of words are defined as a corpus or dictionary of our model. In this study, we state the personality class in Big Five Personality Theory as a class, facet in NEO-PI-R metric as a sub-class, and each composed word into an instance. For better understanding, we show our ontology domain model hierarchy in Fig. 5.

The hierarchy of our ontology model is settled in the bottom-up paradigm since this model starting from specific to general or instances to class [53]. There are no properties needed in personality measurement ontology model. As an instance, from Fig. 5., the words *terluka*, *melelahkan*, *penderitaan*, which means hurting, exhausting, and suffering are classified into vulnerability in Neuroticism class. These words arranged to vulnerability facets because it indicates the feelings of flimsy due to the risk of harm from some experiences.

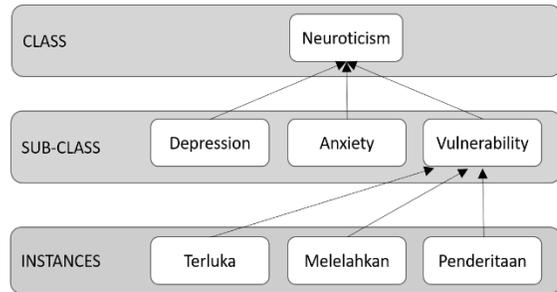


Figure 5: The Hierarchy of Personality Measurement Ontology Model

### 3.4. Model Validation

The validation process is essential to prevent and minimize any bias from the previous classification process. The human assessment approach is an assessment method with the help of domain experts [45]. For this reason, we assign psychologists to validate our classification result before deployment. In this process, the expert ensures that the classified word has entered the correct personality trait according to the Big Five theory and NEO-PI-R metric.

We conduct a human assessment because a human can represent language in terms of circumstances. The words in Bahasa ordinarily have various meanings depending on contextual purposes. For example, the words *bisa* can be represented to “able” or “can” or “poison from the snake.” Hence, we need the psychologist to check and validate the ambiguity of the words that frequently appeared in people's linguistic usage, especially in social media.

### 3.5. Platform Construction

Our platform is designed as an open-source platform to encourage the public or crowds to get involved in model development. People can openly provide some enrichment, correction, and verification of the model. Web-based platform is suitable for our research purposes due to its characteristics compared to other forms such as a mobile app or desktop app. The features of this platform are to measure personality based on the input. The common format of the collection of short text sentences and large-scale text is in comma-separated value (csv); thus, we use this .csv format file as one of our input files. At last, we visualize the result in a radar chart as the output. The platform’s workflow displayed in Fig. 6.

In this research, we utilize Personality Measurement Ontology (PMO) Platform which has been built in our prior research [51]. The platform is running by employing a radix tree algorithm as an effort to sort and parse the sentence, then find the semantic similarities between the input text and the corpus. The pseudocode presented in Fig. 7. The trait calculation is conducted

by finding similar keywords between processed textual data and the existing corpus in the ontology model. If matched, the data then considered representing one or more personality traits depending on the number of keywords that paired.

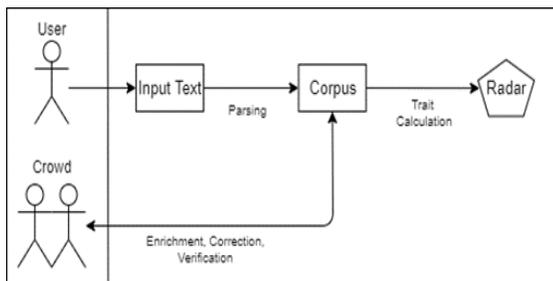


Figure 6: The Platform Workflow

The algorithm of our platform consists of several stages, i.e., convert the model to radix tree, saving database, input processing (sentence and csv format), and trait calculation. The following explanation of each stage are:

1. Algorithm 1: convert the model to radix tree. The established model is sorted using the radix tree algorithm. This algorithm composed of a) csv input file, which a text file contains of collections of keywords, b) a radix tree algorithm named 'tree'; c) an algorithm that is occupied by the data in csv called 'trie'.
2. Algorithm 2: saving database (keywords, traits, and facets). Generate a row for each keyword, facet, and traits into a 'database'.
3. Algorithm 3: input processing (sentence). Parsing sentence by utilizing 'trie'. The result of this process is called 'set\_of\_words,' which contains detected keywords.
4. Algorithm 4: input processing (csv). Parsing csv data into the database. The result is 'set\_of\_word' which loaded by detected keywords.
5. Algorithm 5: trait calculation. Calculate ('set\_of\_word') to get the desired form in the personality measurement results.

```

algorithm 1  convert model to radix tree
input       csv (keywords)
output     radix tree (keywords)
1  csv = input (csv file)
2  tree = new radix_tree
3  for each row in csv do:
   tree <- row.keyword
4  trie <- dump(tree)
5  output (trie)

algorithm 2  saving database (keyword, trait, facet)
input       csv = [keyword, trait, facet]
output     database(keyword, trait, facet)
1  csv = input (csv file)
2  data = [keyword, trait, facet]
3  for each row in csv do:
   data.keyword = row.keyword
   data.trait = row.trait
   data.facet = row.facet
   database <- import(data)
output (database)

algorithm 3  input processing (sentence)
input       sentence
output     result(set of words)
1  array = input(sentence)
2  trie <- load(database)
3  for each word in array do:
   if word is in trie:
     set_of_words <- word
output (set of words)
  
```

```

algorithm 4  input processing(csv)
input       csv(set_of_sentence)
output     result(set of words)
1  csv = input(csv file)
2  load radix_tree
3  trie <- load (database)
4  for each row in csv do:
   for each word in row do:
     if word is in trie:
       set_of_words <- word
output (set of words)

algorithm 5  trait calculation
input       set_of_words
output     result(trait composition)
1  array = input (set_of_words)
2  for each word in array do:
   trait = trait(where facet =
   = word.facet)
   trait += 1
output (trait)
  
```

Figure 7: The Pseudocode of PMO

To facilitate user's convenience, the platform provides a personality measurement process in two ways: 1) by entering textual data such as opinions, statements, or conversations; 2) by uploading the csv file, which consists of numerous textual data. The interface of our platform is shown in Fig. 8.



Figure 8: The PMO Platform Interface

#### 4. Result and Analysis

In order to examine our platform, we measure the personality of the three samples through the platform. We calculate a set of sample tweets in the form of a csv file. The result visualized into a radar chart for getting a better comparison of each personality trait. The measurement results displayed in Table 4.

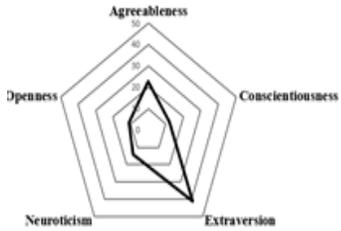
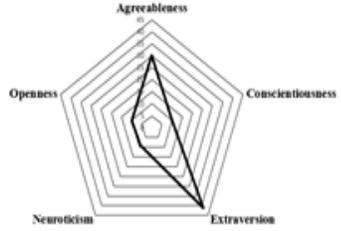
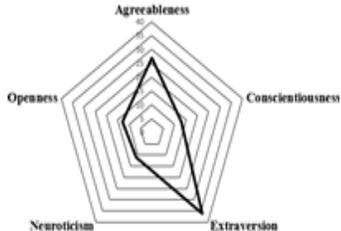
From our measurement result, each sample tends to have one trait as a dominant personality trait. It is a good result because human always has at least one dominant persona over all of the existed character. It also proves that our platform is able to measure all of the traits in the Big Five Personality theory.

As shown in Table 4., our samples have a similar result but not entirely identical. The result also indicates that our samples have a high score in Extraversion personality traits. It means that our samples often show positive feelings, friendliness, and activity-level on their social media activity. For example, @shillicious, who regularly displays his activities, both significant and trivial matters in his daily routine.

The second-highest score of our sample's measurement result is Agreeableness personality trait. This character is representing individuals who have value cooperation and social harmony with another person. @bepe20 is repeatedly showing his compliance and altruism. As a famous professional football player in Indonesia, @bepe20 has a tremendous number of fans. He

generally answers the message of his supporters on social media. He also does not hesitate to praise and welcome others who even he does not know. Thus, this persona makes @bepe20 also has a high score in Agreeableness besides the Extraversion personality trait.

Table 4: The Result of PMO Platform

Account	Result
@jojosuherman	
@bepe20	
@shitlicious	

Even though the platform has proven capacity in measuring personality through linguistic usage, it still has some limitations. Our platform cannot measure complex phrases with different contextual meanings. For example, the sentence *keren gila*, which means he or she expresses a fantastic feeling, is measured into Extraversion and Neuroticism personality traits. The words *keren*, which means impressive, is reflecting Extraversion and *gila*, which means crazy or stupid is representing Neuroticism. That instance shows our platform’s limitation, which only running by mapping word by word. Hence, our platform still needs enrichment and development for measuring sentences with phrases that consist of a different word with different personalities.

## 5. Conclusion

In this research, we explore human’s linguistic usage in social media to build an ontology model for measuring human character. We have successfully implemented the ontology model to a web-based platform for measuring personality automatically. In this study, the ontology form component defined by assigning personality as a class, facet as a sub-class, and words that are referring personality as instances. The platform is generally running well but cannot handle the complex phrases.

Our model helps us to measure human personality in social media. This research significantly contributed to a psychology study, especially in Indonesia. Our model is adequate to support a psychologist to speed-up the personality measurement process. It also can be improved for reading complex phrases by generating another algorithm. Thus, our suggestion for future research is to employ another parsing algorithm such as n-gram for receiving better results. We also suggest enriching the platform’s corpus by engaging the words that are reflecting personality from different social media. Another recommendation is adding weight to each classified word. Since we only measure the frequency of words, and not considering the context of the tweets, adding weight to the indexed words is required to detect context on a sentence.

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