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Association rules mining for job seekers' profiles based on Personality traits and Facebook usage

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Abstract
Personality traits play a significant role in many organizational parameters, such as job satisfaction, performance, employability, and leadership for employers. One of the major social networks, the unemployed derives satisfaction from is Facebook. The focus of this article is to introduce association rules mining and demonstrate how it may be applied by employers to unravel the characteristic profiles of the unemployed Facebook users in the recruitment process by employers, for example, recruitment of public relations officers, marketers, and advertisers. Data for this study comprised 3000 unemployed Facebook users in Nigeria. This study employs association rule mining for mining hidden but interesting and unusual relationships among unemployed Facebook users. The fundamental finding of this study is that employers of labour can adopt association rules mining to unravel job relevant attributes suitable for specific organisational tasks by examining Facebook activities of potential employees. Other managerial and theoretical implications are discussed.

Keywords: association rules mining, Facebook, unemployment, personality traits

Introduction

Digital behaviour and social media users have become a global phenomenon, and Bonanomi, Rosina, Cattuto, & Kalimeri (2017) investigated the pattern of unemployed young Italians. The sample population focused on 1858 unemployed, not currently in school, not currently under any form of training citizens, intending to construct a classification model for future prediction of the employment status of other citizens. According to Rosina et al. (2017), the research developed a Facebook application, 'LikeYouth,' which function was to collect information on the sample population to assess their morality and personality on a variety of world views. The collected data was then used to train a machine learning classification model that can leverage the digital data of any other citizen, outside the study sample to predict their employment status. The developed model was reported to have a predictive accuracy of 61%. Meanwhile, a report by Sampson (2014) suggests that Google search results for "Facebook" indicate a strong correlation with unemployment figures. According to Sampson (2014), this correlation was interpreted by Bloomberg to mean that unemployed persons engage in Facebook use as a way of passing the time or connecting with others who might help them find a job.

The focus of this article is to introduce ARM and demonstrate how employers may apply it, to unravel the characteristic profiles of the unemployed Facebook users in the recruitment process by employers (e.g., recruitment of PRO's, marketers, advertisers). Realizing that employers do a background check on individual Facebook profiles of potential candidates seeking employment in their organization, this study will be relevant and useful to such organizations and researchers. This study employs Association Rule Mining (ARM) for mining hidden but interesting and unusual relationships among unemployed Facebook users to achieve the set goals (Liu, Zhai, and Pedrycz, 2012; Feng et al., 2016). Much research has been done in the area of Web usage clustering, with the issues involved in data mining for extraction of web navigation patterns, ordering relationships, prediction of web surfing behavior, and clustering of web user sessions based on weblogs. Some used the techniques of weblog data mining with cookies, while data mining techniques are also used to search for improvement in blogs (Bhadoria, (2011). Data mining techniques have been adopted in previous studies such as in Bhadoria (2011), Wazurkar, Bhadoria, & Bajpai (2017) and Bhadoria, & Chaudhari (2019).

One of the major social networks, the unemployed derives satisfaction from is Facebook. Since the global economic crisis in 2008, the world's unemployment rate has declined by 5 percent, which is projected by the International Labor Organization to remain substantially constant over the next few years. The International Labor Organization reports reveal that slightly more than 172 million people globally were unemployed in 2018, which is about 2 million less than the year 2017. Regionally, the ILO reports only 4.5 percent of Sub-Saharan Africa's working-age population is unemployed, with 60 percent employed. The research revealed that these useful statistics are deceptive because, in sub-Saharan Africa, 18 of the top 20 countries with the highest rates of poverty are considered to have 60 percent employment in the informal sector. Globally, 48 percent of females are employed, compared to 75% of males, with 20% of young people under 25years being unemployed.

Globally, both the employed and unemployed individuals have structures and propensities (Personality traits) that explains their thought patterns, behaviour, and emotions (Colquitt, 2009). Uncontrolled emotions and behaviour of the unemployed bring about tensions and challenges which affect their inter/intrapersonal relationships and interactions. Personality traits play a significant role in many organizational parameters such as job satisfaction and performance, employability, and leadership for employers. Research reveals the association of personality traits to these performance parameters and understands these relationships.

This study provides insight into understanding the role of personality traits among the Nigerian job seekers and employers by innovatively conducting association mining rule using Facebook users' profile. The application of association rules, which is a data mining technique to discover hidden knowledge regarding personality traits of unemployed Facebook users and their social behaviour, is novel. This study, to the best of the authors' knowledge, is new in the context of Nigeria. Hence, it contributes to the existing body of knowledge by unravelling the behaviour of employed Nigerian on the usage of Facebook social media. It also provides insight to employers who are interested in conducting background checks of prospective employees regarding their social characteristics, revealing the situation of unemployment in the context, which can be useful for policy formulation that can address the unemployment issues in Nigeria. Besides, the study critically investigated the unemployed profile and their personality traits, association skillsets, social support, and satisfaction.

The study orders the remaining sections of this article as follows. The next segment is a review of the method of ARM and related concepts/nomenclature. Then, the results and discussions are provided based on the data. The study touches on the implications of the job-seeking issues and discussed the limitations and proposed future research.

Facebook Users in Nigeria

Facebook has become a point of social connection for the Nigerians. According to Olaleye, Sanusi & Salo (2017), Nigeria is one of the leading Facebook users in Africa. A survey and forecast conducted by Statista (2019) between 2017 and 2018 indicated that the number of Facebook users in Nigeria would get to 30.4 million in 2023 from a total of 20.7 million users recorded in 2017. These estimates leverage users who access their Facebook accounts through any device. Irrespective of the number of times the users logged into their accounts within a month. In another survey conducted by Internet World Stats (2019), internet users in Nigeria grew from 200,000 as at 31st December 2000 to above 111 million as at 31st March 2019. Out of this number of internet users, 17 million were said to be Facebook subscribers as of 31st December 2017. According to Internet World Stats (2019), the data used in the investigation was sourced from Worldwide Worx, ITU, and Facebook.

According to Sampson (2014), this correlation was interpreted by Bloomberg to mean that unemployed persons engage in Facebook use as a way of passing the time or connecting with others who might help them find a job. Even though Facebook use has penetrated the Nigerian market over the years, no literature suggests a cohort study has been conducted earlier to establish a link between Facebook use and unemployment in the Nigeria context. This study addressed this gap.

Unemployed Facebook Users' Five Personality Traits, Online Social Support, and Satisfaction

Unemployment is a state of joblessness, and it could be a frictional unemployment as a condition that warrants unemployed person to switch jobs, seasonal unemployment that indicate a situation of seasonal joblessness, structural unemployment that brings jobs to an end due to lack of a specific skillset and cyclical unemployment as a condition of joblessness due to weak economy. Unemployment can lead to a psychological problem, affect the economy and workforce development. This study carefully reviewed the literature to look at the relationship of five personality traits, online social support, and Facebook satisfaction (Figure 1 shows our proposed general model).

Agreeableness

Agreeableness is one of the five personality traits of the Big Five personality theory. Within the Big five model of personality, agreeableness is a trait-dimension associated with the tendency to behave prosocially; highly agreeable people tend to be highly cooperative and altruistic (Haas, Ishak, Denison, Anderson & Filkowski, 2015). Agreeableness is one trait-dimension associated with prosociality (Graziano & Tobin, 2013) and is negatively associated with anger, aggression, and interpersonal arguments (Meier & Robinson, 2004). In the workplace, agreeableness is beneficial in occupations requiring considerable interpersonal interaction and helping others (Barrick, Mount, & Judge, 2001) and is particularly important in social domains (Jensen-Campbell, Knack, & Gomez, 2010). According to Asendorpf & Wilpers, (1998); Soldz & Vaillant, (1999), agreeableness is uniquely predictive of social support and harmonious relationships. There is empirical evidence that agreeableness is associated with social–cognitive functions that include empathy, the theory of mind and perspective taking (Côté et al., 2011; Kraus, Côté, & Keltner, 2010).

Conscientiousness

Conscientiousness is a personality trait because of its inclusion in the Big Five taxonomy of personality traits (Goldberg, 1993). Conscientiousness denotes being mindful of those around you; thus, people with higher levels of conscientiousness tend to be empathetic towards other people (Melchers et al., 2015), including strangers. Conscientiousness is a spectrum of constructs that describe individual differences in the propensity to be self-controlled, responsible to others, hardworking, orderly, and rule-abiding (Roberts, Jackson, Fayard, Edmonds, & Meints, 2009). Conscientiousness spectrum, such as impulse control, are both changeable and continue to develop and change well into adulthood (Jackson et al., 2009; Roberts, Walton, & Viechtbauer, 2006). Thus, the levels of conscientiousness can be increased (Roberts, Hill, and Davis, 2017) and can be low (Toegel G, Barsoux JL 2012). Besides a slight decrease between early and mid-adolescence, we grow more conscientious with age (Van den Akker, 2014). Conscientiousness has formerly been shown to be negatively related to the use of the Internet and other forms of CMC (Butt & Phillips, 2008; Swickert et al., 2002).

Conscientiousness is more likely to avoid CMC tools, which may serve as procrastination or distraction tools from their daily tasks. Conscientiousness plays a role in majority of the significant domains of life and one of the most reliable predictors of leadership (Judge, Bono, Ilies, & Gerhardt, 2002), academic achievement (Noftle & Robins, 2007), marital stability (Roberts & Bogg, 2004) or divorce (Roberts et al., 2007) and an independent predictor of major depression over and above other personality traits, such as neuroticism (Kendler & Myers, 2010). Conscientiousness reflects the relatively enduring, automatic patterns of thoughts, feelings, and behaviours (Lebowitz, 2016a) that differentiate individuals from one another and that are brought to light in trait-evoking situations (Roberts, 2009; Roberts & Jackson, 2008). Although 40% to 50% of conscientiousness-related traits are heritable (Krueger & Johnson, 2008), most of its variance can be attributed to environmental influences (Krueger & Johnson, 2008). Conscientiousness is conceptually relevant because it helps to identify environments in which the traits (Bandura, 2012; Jackson, Hill, & Roberts, 2012) can be expressed.

Social support corresponds to physical (Berkman, Glass, Brissette, & Seeman, 2000; Cohen, 2004), cognitive (Seeman, Lusignolo, Albert, & Berkman, 2001), and health benefits. Socially engaged individuals tend to increase on traits that allow for success in these engagements, such as conscientiousness (Lodi-Smith & Roberts, 2012). Jackson et al., 2010). Thus, becoming more conscientious may prove one vehicle by which to maintain social support and relationships because low conscientiousness can bring about social disintegration (Hassan, A., Zain, Z., & Ajis, M. (2019). Unemployment significantly inhibits opportunities to express conscientiousness and cut-off access to previously valued achievement goals and precipitate changes in conscientiousness. Retirement from employment and first-time entry into employment have been associated with changes in conscientiousness (Specht et al., 2011). However, being in paid work has been linked to changes in social responsibility (Roberts & Bogg, 2004).

Extraversion

In human personality theory, extraversion is one of the five personality traits (McCrae & Costa, 1999). It is a behavioural manifestation whereby an individual enjoys socializing with people rather than staying alone. Someone who possesses the characteristics of extraversion as a personality trait is referred to as an extrovert. Extraversion, alongside with the other personality traits, according to Psychologist World (2019), was popularized by Swiss psychologist Carl Jung in 1921. Extraversion is considered as one of the higher-order dimensions of personality traits and regularly found to be in the different dimensional models of personality traits (Vinkhuyzen et al. 2012). According to Eaves and Eysenck (1975), extraversion depicts “the degree to which a person is outgoing and interactive with other people.”

Some of the characteristic manifestations of extraversion, according to Vinkhuyzen, et al. (2012) includes the tendency for an increased level of sociability, activity, positive emotions, and sensation drive. For instance, a low level of extraversion can be caused by social phobia. Research has shown that extraversion is related to positive affect (McCrae & Costa, 1999; McCabe & Fleeson, 2012). Harari et al. (2018) assert that the five personality traits influence job satisfaction. According to Jia et al., (2015), “extraversion had a significant positive relationship with social support.” They further assert that individuals with high scores on extraversion are expected to better engage with social support. Similarly, research shows that extraversion influences and instantiate happiness through social support, and seeking social support tends to correlate positively with extraversion (Tan et al., 2018; Halamandaris & Power, 1999).

Neuroticism

According to Digman (1990), neuroticism is one of the big five personality dimensions. McCrae et al. (1999) affirm that neuroticism is an essential trait of personalities. It serves as a risk factor for psychopathology; it is often used to examine psychological disorders like depression, anxiety, shame, and social phobia. Similarly, neuroticism is used to examine other problems such as personality disorders, eating disorders, and schizophrenia (Kotov et al., 2010; Ormel et al., 2013). The second theory, BIS, and BAS is proposed by Gray (1991). People with high neuroticism do have unstable emotions, and they are aggressive, especially when they encounter stress. Wang et al. (2011) found that working men with high neuroticism became active and aggressive socially when they had job stress. Likewise, their study showed that men with low neuroticism became silent and inactive socially when they experienced job stress. These scholars termed low neuroticism people as stable emotional persons and vice versa. Similarly, the study of Joanne et al. (2003) showed that people with high neuroticism would develop many depressive symptoms and conditions of these people might be deteriorated if they experienced marriage distress. The findings of the above studies were noted in the work of Furr and Funder (1998), who previously argued that high neuroticism usually leads to personal negativity. Furr and Funder (1998) explained that personal negativity arises from low self-esteem, dissatisfaction with life, and unhappiness. Thus, a high level of neuroticism makes people unstable emotionally, act aggressively, inactive socially, depressed, ashamed, display unnecessary anger, unhappy, have low self-esteem, and develop personal negativity.

Openness

Openness is one of the five personality traits of the five-personality theory. Researchers sometimes call it openness to experience. Openness measures people's originality and open-mindedness (Cukic and Bates, 2014). Openness has the most substantial impact on innovations out of all the personality traits. Weele, 2013 stated some of the characteristics associated with openness as a personality trait, and they are; open-mindedness, adventurousness, intellectual curiosity, imaginativeness, information-seeking behaviour and multiple of interests (Bozionelos et al 2014). All these characteristics help to empower the individual who has a very strong openness trait and enables them to involve in both new challenges and experiences (Rossberger, 2014). A person with a high level of openness to experience in a personality test enjoys trying new things, and these sets of people are imaginative, curious. However, open-minded but individuals who are low in openness to experience would instead not try new things, and this set of people that fall into this category are close-minded, literal, and enjoy having a routine.

Woo et al. (2014) introduced a three-level structural model of openness to experience. This model was derived from a factor analysis of 36 existing measures of openness-related scales, which yielded six facets. The first face centered on *intellectual efficiency* (i.e., processing novel stimuli quickly, remembering information, being knowledgeable and intellectual). The second dwell on *ingenuity* (i.e., mental agility in manipulating ideas or concepts, refining existing information, creating something entirely new). The third focus on *curiosity* (i.e., being inquisitive, perceptive, desiring to learn about scientific principles and related topics). The fourth on *aesthetics* (i.e., appreciating various forms of art, open to aesthetic experiences) The fifth on *tolerance* (i.e., enjoying learning about different cultures, attending cultural events, befriending people from other cultures, immersing oneself in a foreign culture when travelling), and the final one on *depth* (i.e., desiring to gain insight into self/world and to self-improve, discussing philosophy, self-reflecting, meditating).

Social Support

There are different ways and manners each personality trait responds to social support. People who are actively open tend to identify or deal with the increasingly troubling problem of biased or false information available on social media (Maheshwari, 2016; El-Bermawy, 2016). The active open-minded individual also moderates the extent to which people are open to new perspectives, and viewpoint, instead of treating their social media spaces as "echo chambers" which merely reinforce and ossify their pre-existing views and values (Barbera et al. 2015; Dehghani et al. 2016). Open-minded people think more deeply about information, and they are also likely to recognize and ignore unsubstantiated or false information online (Starbird et al., 2014). A promising step in this direction has been recently reported by Bronstein (2018), found out that active thinkers are positively associated with their ability to distinguish between 'fake news' headlines from real headlines.

Life satisfaction and effects of unemployment on an individual

Human personality have been shown to change due to several factors such as intrinsic maturation processes conveyed by genetic component (McCrae & Costa, 2008), environmental component (Kandler, 2012), contextual factors (Boyce et al. 2015) and the continuous interactions between person and the environment (Roberts, Wood, & Caspi, 2008). The effect of personality changes could be visible in commonly occurring life events, for example, social life, quality of marriage and relationships (Neyer & Lehnart, 2007; Roberts & Bogg, 2004; Watson & Humrichouse, 2006), following unemployment (Boyce, et al., 2015), variations in marital level (Specht, Egloff, & Schmukle, 2011), workplace experiences (Roberts, Caspi, & Moffitt, 2003), and during retirement (Specht et al., 2011). For example, Boyce, et al. (2015) hypothesized that the unemployment situation could propel variations in personality to produce diverse manners of thinking, feeling, and behaving. Furthermore, unemployment is probable to encourage stress and entail troubling conditions (Dooley et al., 2000), which may result in the feeling of low self-confidence and seclusion (Heinrich & Gullone, 2006). Studies have shown that becoming unemployed has an undesirable effect on life satisfaction. People without the experience of unemployment had higher life satisfaction than those with at least one-year experience of unemployment (Boyce, Wood, & Brown, 2010).

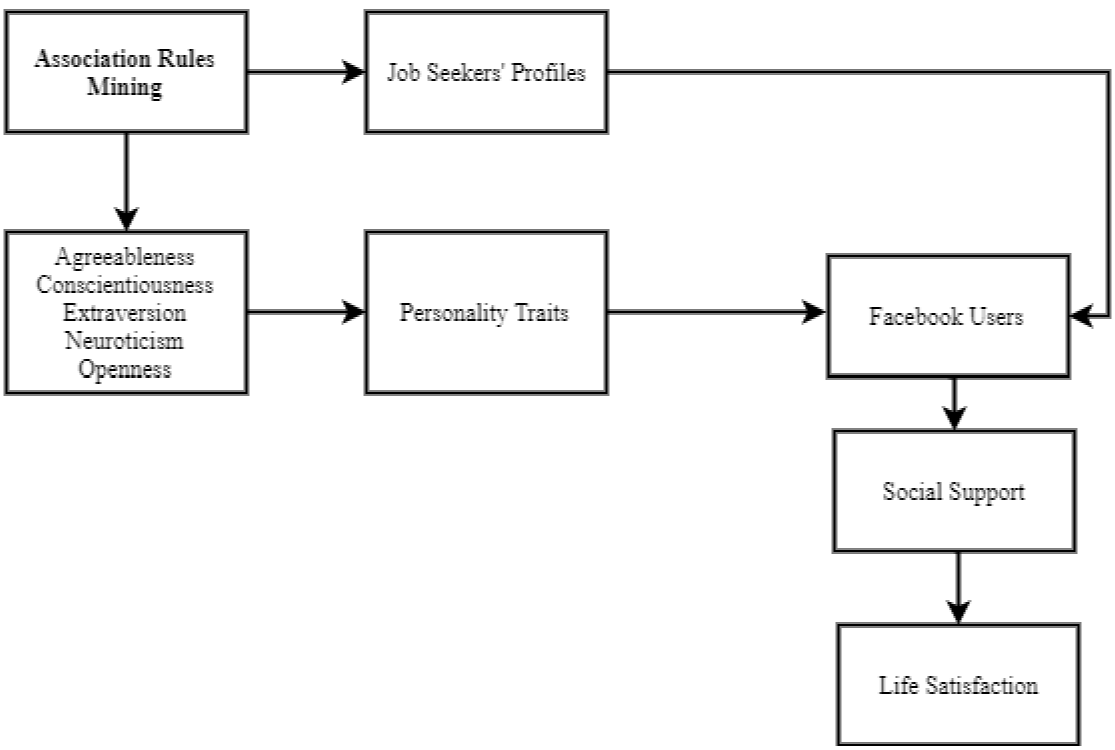

Figure 1: Job Seekers' Conceptual Framework

Table 1: Social media comparison for job seekers

	Facebook	Twitter	LinkedIn	Instagram	Pinterest	YouTube	Social Media
Number	15	11	10	5	1	7	2

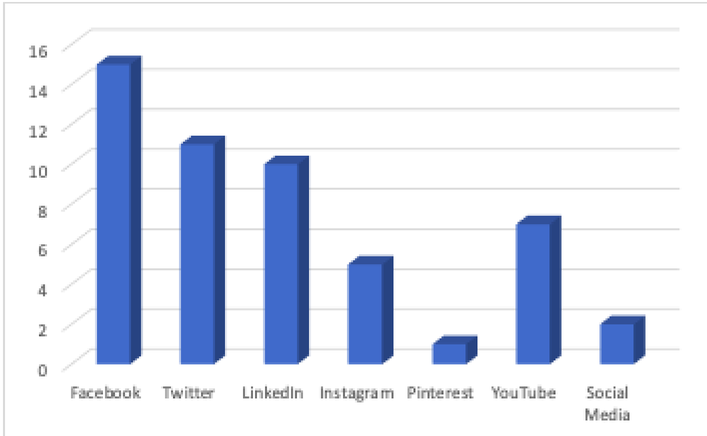

Figure 2: Comparison with other social media App

This study used secondary data to compare the use of Facebook by job seekers with other social media apps like Twitter, LinkedIn, Instagram, and others, see Table 1 and Figure 2 above. In our comparison, Facebook had the highest usage, as depicted in the diagram above. Our work was motivated by the fact that Facebook is the most widely used social media platform in Nigeria. The platform is heavily subscribed by about 60% of social media users in Nigeria (Statcounter, 2019). While this work is novel in the context of Nigeria, there are similar works in the other parts of the world. While comparing our findings with other earlier studies, Van de Ven and Bogaert (2017) conducted similar research to examine if profiles from a job-related LinkedIn could be used to form impressions of a profile owner's self-rated personality accurately. Of the 97 employees from the Dutch human resources development company, the researchers found that the LinkedIn profile allowed for better inferences of extraversion and self-presentation of the profile owner. The study implied that employers are 1.5 times more likely to select people with higher trait extraversion as compared to people with lower trait extraversion. In a related study, Tighe & Cheg (2018) collected data from 250 Filipino Twitter users to study their personality traits. The study modelled the personality traits of twitter users. The model is text-based, which explores how the people of the Philippines speak irrespective of the language. The researchers performed regression and classification data analysis and found conscientiousness as the easiest trait to model, followed by extraversion while personality traits such as openness, agreeableness, and neuroticism were found to be challenging to model. However, the classification models for agreeableness and neuroticism had subpar performances but performed better than those of openness.

Strength and Weakness of Social Media Online App

Several studies have reported the strengths and weaknesses of some social media apps. For instance, Gonzalez-Ramirez, Gasco, & Taverner, (2015) reported that the major strength of the Facebook app is its support for direct and synchronous communication among users. This direct communication feature enables business owners to engage their audience directly through Facebook for adverts and feedback. One of the main weaknesses of Facebook is related to privacy concerns. The app is porous such that ideas and information shared through the platform are accessible to the general public, including potential adversaries. According to Soboleva, Burton & Khan, (2015), Twitter has features that are useful in promoting products and monitoring campaigns. The use of hashtags and embedded web links supports instantaneous retweeting that enables information to be disseminated at a very fast pace. While the fast-paced nature of Twitter is considered one of the strengths of the app, it could also be a drawback as social media makes it difficult for some users to be carried along without missing out on some vital information on a trending topic. In addition to this weakness, a tweet is limited to just 140 characters, which might not be enough to convey a meaningful chunk of information in some instances.

Model Comparison

We evaluate this predictive study model with alternative models of existing literature on job seeking. We noticed similarities and divergences. This study integrates five personality traits through the association rules mining to express the impact of job seekers' profiles that form the group of Facebook users and show how Facebook users seek social support to get life satisfaction while seeking jobs. In comparison with our proposed model, Suki, Ramayah and Ming, (2010), in explaining the job searching process through the social networking sites revealed that perceived usefulness and perceived enjoyment are related to the behavioural intention to use online social networking sites significantly, but perceived ease of use was insignificant. In the same line, Burke and Kraut (2013) used mathematical modelling to investigate how communication with differs ties predicts improvements in stress, social support, and how they bridged social capital and the possibility of finding new jobs. Communication with strong ties has a higher predictive of finding employment than weak ties in their study. Unlike the earlier mentioned models, El Ouirdi, Segers, El Ouirdi and Pais, (2015) combined the theory of hyperpersonal computer-mediated communication, self-efficacy, and social exchange to study the job seekers' professional online image concerns. In their study, they discovered that career-oriented self-disclosure was predicted by social media self-efficacy, professional online image concerns, work experience, gender, and social media effectiveness while demographics such age, educational level, and employment status were not significant. Also, Ryu (2018) built a model to predict the unemployment rate through social media analysis. All the models examined are similar to our study based on a prediction technique but differed in the statistical data analysis approach. Other studies used structural equation modelling approach, linear multilevel modelling, hierarchical multiple regression, part-of-speech tagging, and sentiment analysis techniques while our study employed association rules mining for hidden mining relationships between five personality traits, social support, and life satisfaction.

Materials and Methods

Association rules

Association rules analysis is a technique of machine learning data mining, which originates from retail and marketing. Association rule data mining technique has been employed in retail and marketing to comprehend which products are often bought in combination with one another Sutch, (2015). The use of association rules is much more suitable to the initial exploration of uninvestigated data, to enable hypotheses to be formulated that can be investigated by employing other methods Sutch, (2015). In many areas of research, association rules are commonly employed for mining hidden but interesting and unusual relationships among several data objects in a specified dataset (Liu, Zhai, and Pedrycz, 2012; Feng et al., 2016). Fundamentally, the association rule technique is used to depict attributes value conditions that occur not infrequently together in a given dataset. Association rules proffer information in the form of "if-then" statements where the antecedent (the "if" part) and the (the "then" part) forms the consequent which, are probabilistic. Additionally, association rule has basically two numbers that express the degree of unpredictability about the rule.

Support: In association rule, support is the number of transactions that captures all items in the antecedent and consequent parts of the rule which is usually expressed as a percentage of the total number of records in the database (Ghafari and Tjortjis, 2019; Huang, Li, and Duan, 2011).

Confidence: The ratio of the number of transactions that captures all items in the consequent as well as the antecedent to the number of transactions that include all items in the antecedent is often termed, Confidence (Ghafari and Tjortjis, 2019; Huang, Li, and Duan, 2011).

Lift: Lift is nothing, but Lift is a value that provides information about the increase in the probability of the consequent given the antecedent part. Thus, the ratio of confidence to expected confidence.

A rule is a notation consisting of two parts, a left-hand side (LHS) and a right-hand side (RHS), as shown in (Li et al., 2018).

Materials

The materials going to be deployed in this investigation are presented in this section. These include association rules, measures of strength of rules, apriori algorithm, and the experimental dataset. Association rules are widely used for mining hidden but interesting relationships among data objects in a dataset (Feng et al., 2016; Liu, Zhai, and Pedrycz, 2012). This technique is used in market basket analysis, where the regularities between items purchased at supermarkets are explored. For instance, an established association rule might read, “customers who purchase milk are 80% likely also to purchase bread”. A rule is a notation consisting of two parts, a left-hand side (LHS) and a right-hand side (RHS), as shown in Equation (1) (Li et al., 2018).

(1)
$$\left.\begin{array}{l} Rule1: itemsetX \Rightarrow itemsetY \\ Rule2: \{bread, butter, sugar\} \Rightarrow \{milk\} \end{array}\right\}$$

This is interpreted as, the item(s) on the RHS were frequently purchased alongside item(s) on the LHS. The strength of a rule is decided by three measures: support, confidence, and lift (Hu and Chen, 2006). Consider $Rule1$ in Equation (1), support is the ratio of the number of transactions containing both X and Y to the total number of transactions in the dataset. This rule is given by Equation (2)

(Ghafari and Tjortjis, 2019; Huang, Li, and Duan, 2011).

(2)
$$Support = \frac{\text{Number of transactions with both X and Y}}{\text{Total number of transactions}} = P(X \cap Y)$$

With support, the percentage of transactions containing a given itemset can be evaluated from the dataset.

Confidence measures the likelihood of item Y being purchased whenever item X is purchased (Ghafari and Tjortjis, 2019; Huang et al., 2011). Confidence is evaluated, as shown in Equation (3).

$$Confidence = \frac{\text{Number of transactions containing both X and Y}}{\text{Total number of transactions with X}} = \frac{P(X \cap Y)}{P(X)} \tag{3}$$

The lift measures the likelihood of item Y being purchased whenever item X is purchased while putting into consideration the popularity of both. A lift value of more than 1 shows that the occurrence of X is positively related to the occurrence of Y. That is, X and Y occur more often together than expected. When lift value is less than 1, it is interpreted that the chances of X occurring together with Y are minimal. A lift value close to 1 indicates that X and Y appear almost often together as expected. The formula for computing lift is given in Equation (4) (Soysal, 2015).

$$Lift = \frac{\text{Confidence}}{\text{Expected Confidence}} = \frac{P(X \cap Y)}{P(X).P(Y)} \tag{4}$$

Apriori Algorithm is one of the algorithms used in iteratively mining association rules from a given dataset (Li et al., 2018). The algorithm works as presented in the following steps: Generate frequent item sets of length one and repeat this step until all frequent item sets have been identified. Then, iteratively generate frequent item sets of length k+1 from those of length k and prune the candidate item sets that contain subsets of length k, which are not frequent. Again, scan the dataset and count the support of each candidate item set, eliminate infrequent candidate item sets, and leave out frequent ones.

Experimental Dataset

The dataset used in this investigation consists of 3000 observations and 42 fields encompassing measurements about a personality trait, online social support, self-disclosure, satisfaction, and continuous use. The items relating to the five items that measure personality trait (conscientiousness, neuroticism, agreeableness, openness, and extraversion) are prefixed in the dataset as CON, NEU, AGR, OPE, and EXT respectively. The items on online social support are prefixed with OSS, while the self-disclosure items take SED prefix. Relatedly, the satisfaction and continuous use items are prefixed as SAT and CONT, respectively. The detailed item definitions are presented in Appendix 1.

Methods

a. *Conversion to Transaction Dataset*

Originally, the data used in this study was generated from participants using the 5-point Likert scale. This means that the data points consisted of values over the range of 1 to 5. Notably, transaction data has only two possible values: 0 indicating when an item was not purchased and 1 indicating an item was purchased. In order to convert the 5-point data points to binary, the min-max normalization method (Pandey and Jain, 2017; Jain, Shukla, and Wadhvani, 2018) was deployed. This method is used to scale a dataset in such a way that all values are coerced to the range [0, 1], with mean 0 and standard deviation 1. After the min-max normalization was executed on the experimental dataset, all data points less than 0.5 were coded as 0, and those greater than or equal to 0.5 were coded as 1. This effectively converted the data to a transaction's dataset. A data point having 0 as an entry means the respondent measures negative in the quality being assessed, while 1 means the respondent measures positive. For the purpose of this study, a combination of all responses over the 43 fields for each participant constitutes a transaction, and each field is a transaction item. There are 3000 records in the dataset, which means the transaction dataset consists of 3000 transactions.

b. *Dataset Properties*

Some properties of the transaction dataset are examined in this section.

- Item frequency

The most frequent 15 items in the dataset are shown in the frequency plot in Figure 3.

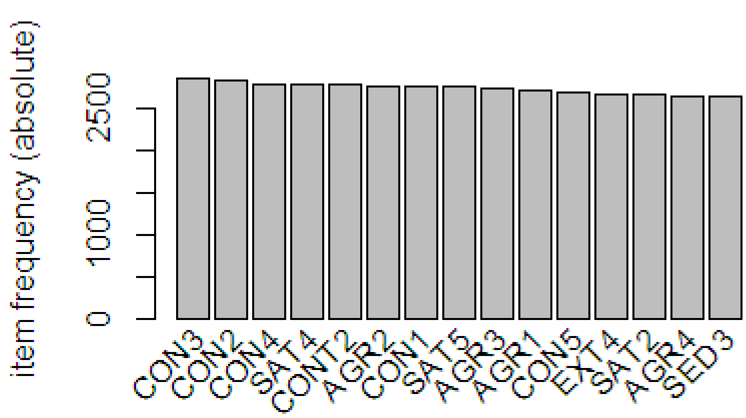

Figure 3: Item frequency plot for 15 most frequent items

In the Figure 3, the most frequent 15 items appearing positive in the 3000 transactions are shown, including the number of times they appear in the dataset.

- Item frequency with support

The most frequent 15 items and their support are presented in Table 2.

Table 2: Most frequent 15 items and their support

AGR1	AGR2	AGR3	AGR4	AGR5
0.9026667	0.9236667	0.9100000	0.8850000	0.7366667
CON1	CON2	CON3	CON4	CON5
0.9230000	0.9470000	0.9513333	0.9326667	0.8943333
CONT2	CONT3	EXT1	EXT4	
0.9276667	0.7976667	0.8350000	0.8893333	

The values in Table 2 could be interpreted to mean that, in the entire dataset, 90% of all participants measured positive in AGR1, while 85% measured positive to EXT5.

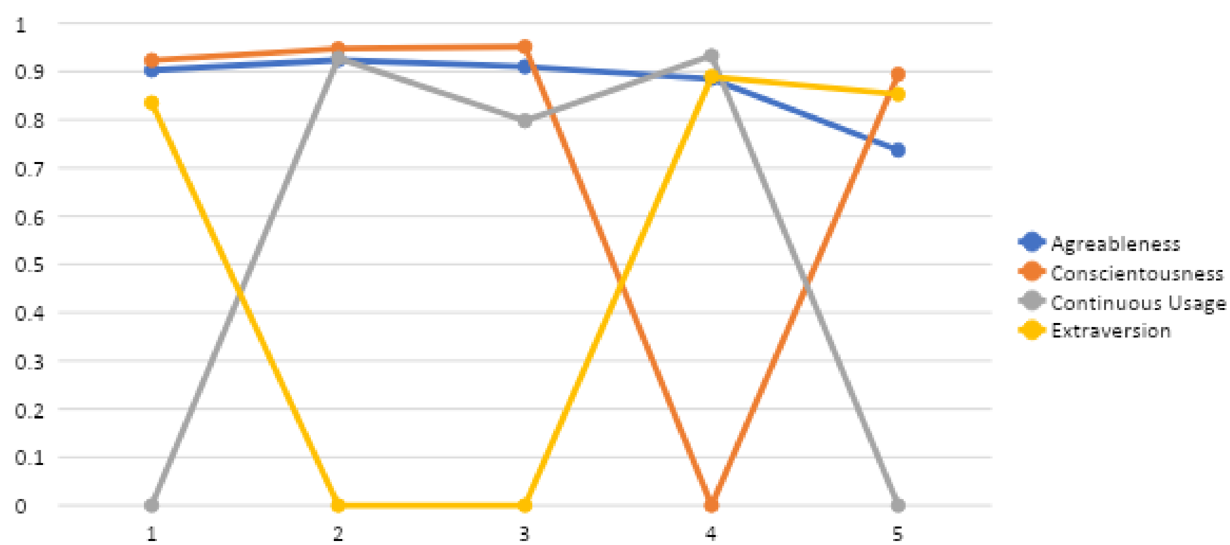

Figure 4: Graphical representation of the most frequent 15 items and their support

The association rules generated in this investigation are shown in Table 3. Using minimum support of 0.65, 12 strongest rules were generated as shown.

Results

From Table 3, Rule 1 is interpreted to mean that participants who measures positive to CON3 also measured positive to CON1, CON2, and CON4. The support of 0.835 indicated against this rule means that 83.5 percent of all the 3000 participants who measured positive to CON1, CON2, and CON4 also measured positive to CON3. By implication, the confidence value of 0.98 shown against this rule indicates the likelihood that 98% of people in whichever population sample who measure positive to CON3

will always measure positive to CON1, CON2, and CON4. While support specifically evaluates strength of a rule based on an experimental dataset, confidence generalizes about the likelihood of what the outcome will be using any population sample. In each of the rules, the lift value is greater than 1. This indicates that the chances of the LHS occurring together with the RHS, will always be more than expected in any investigation.

Table 3. Association Rules

Rule No	LHS		RHS	Support	Confidence	Lift
1	{CON1,CON2,CON4}	=>	{CON3}	0.8353	0.9824	1.0326
2	{AGR2,CON1,CON4}	=>	{CON2}	0.7987	0.9824	1.0373
3	{CON1,CON4,SAT4}	=>	{CON3}	0.7967	0.9831	1.0334
4	{CON1,CON5,CON4}	=>	{CON3}	0.7887	0.9830	1.0333
5	{AGR1,CON1,CON4}	=>	{CON3}	0.7780	0.9827	1.0330
6	{CON1,CON4,SED3}	=>	{CON3}	0.7617	0.9824	1.0326
7	{CON1,CON4,EXT5}	=>	{CON3}	0.7323	0.9830	1.0333
8	{CON1,CON4,OSS4}	=>	{CON3}	0.7303	0.9830	1.0332
9	{CON1,CON4,CON4}	=>	{CON3}	0.6883	0.9838	1.0341
10	{CON2,CON4,OPE3}	=>	{CON3}	0.6667	0.9823	1.0326
11	{CON1,CON4,OPE1}	=>	{CON3}	0.6547	0.9850	1.0353
12	{CON1,CON4,OPE3}	=>	{CON3}	0.6510	0.9854	1.0358

Discussion

Association rules mining were generated to determine the characteristics of personality traits, online social support and the self-disclosure items. For clarity, 12 sets of rules with a support of 0.65 is presented separately in Tables 3. Only a selection of high-support and high-confidence rules significant to the present study are depicted for brevity, and implications for further research on personality traits of Facebook users. Table 3 shows the strong rules which are created by performing association rule mining via Apriori algorithm on 42 different types of measurements about personality traits, online social support and self-disclosure items; these strong association rules are described below:

Rule 1; If an individual is always prepared (CON3), then the same individual will carry out his plans (CON1), pay attention to details (CON2) and make plans and stick to them (CON4). From Table 3, Rule 1 is interpreted to mean that participants who measures positive to CON3 also measured positive to CON1, CON2, and CON4. The support of 0.835 indicated against this rule means that 83.5 percent of all the 3000 participants who measured positive to CON1, CON2, and CON4 also measured positive to CON3. By implication, the confidence value of 0.98 shown against all the rules (rule 1 to rule 12) indicates the likelihood that 98% of observations with whichever population sample will exhibit the associations portrayed by this rule.

Rule 2; Provided that an individual pays attention to details (CON2), then such individual will be concerned about others (AGR2), the same individual will carry out his plans (CON1), and also make plans and stick to them (CON4). The strength of this rule shows that 79.8% of observations complied with this interrelationship.

Rule 3; On the assumption that an individual is always prepared (CON3), then the same individual will carry out his plans (CON1), will recommend people around him/her to use Facebook (SAT4) and make plans and stick to them (CON4). These qualities occurred together in 79.6% of the observations and we are confident that they will occur together in 98 out of every 100 times.

Rule 4; With the condition that an individual is always prepared (CON3), then the same individual will carry out his plans (CON1), I am exacting in my work (CON5) and make plans and stick to them (CON4). A total of 78.8% observations had these qualities combined.

Rule 5; Whenever an individual is always prepared (CON3), then the same individual will carry out his plans (CON1), will sympathize with other feelings (AGR1) and make plans and stick to them (CON4).

This suggest that 77.8% of individuals who are always prepared, satisfy these properties considered as a whole.

Rule 6; Supposing that an individual is always prepared (CON3), then the same individual will carry out his plans (CON1), would like to use Facebook to express his/her personality (SED3) and make plans and stick to them (CON4). This connotes that 76.1% of the observations fits into this supposition

Rule 7; On the occasion that an individual is always prepared (CON3), then the same individual will carry out his plans (CON1), wouldn't mind being the center of attraction (EXT5) and make plans and stick to them (CON4). These occasions happened together in 73.2% of the considerations.

Rule 8; Granted that an individual is always prepared (CON3), then the same individual will carry out his plans (CON1), will use Facebook to talk to a knowledgeable individual about job opportunities (OSS4) and make plans and stick to them (CON4). The presupposition is that 73.0% of the observations satisfies this evidence

Rule 9; Conceding that the case that an individual is always prepared (CON3), then the same individual will carry out his plans (CON1), will exact in their work (CON5) and make plans and stick to them (CON4). A total of 68.8% evidences had these qualities put together.

Rule 10; Assuming, that an individual is always prepared (CON3), then the same individual will enjoy hearing new ideas (OPE3), pay attention to details (CON2) and make plans and stick them (CON4). These properties occurred together in 66.6% of the observations.

Rule 11; Wherever an individual is always prepared (CON3), then the same individual will carry out his plans (CON1), will get excited by new ideas (OPE1) and make plans and stick them (CON4). The power of this rule reveals that 65.4% of observations complied with this interrelationship.

Rule 12; Contingent upon the fact that an individual is always prepared (CON3), then the same individual will carry out his plans (CON1), will enjoy hearing new ideas (OPE3) and make plans and stick them (CON4). The presupposition is that 65.1% of the investigations satisfies this contingent.

Again, considering Rules 2 through to 12, the support values ranging from 0.651-0.798 indicated against each rule means that 65.1-79.8 percent of all the 3000 participants who measured positive to a specific item in the (LHS) also measured positive to its (RHS). Similarly, by implication, the confidence value of minimum 0.98 shown against all the rules indicates the likelihood that 98% of conscientious people in whichever population sample who are always prepared (CON3) will always carry out their plans (CON1), pay attention to details (CON2) and also make plans and stick them (CON4). While support specifically evaluates strength of the rule based on our experimental dataset, confidence generalizes about the likelihood of what the outcome will be using any population sample. In each of the rules, the lift value is greater than 1. This indicates that the chances of the LHS occurring together with the RHS will always be more than expected in any investigation.

As we demonstrate through this article, sentences/phrases can be studied using a survey to discover their correlations in populations that uses Facebook. The focus of this article is thus to introduce ARM and demonstrate how it may be applied by employers to unravel the characteristic profiles of the unemployed Facebook users in the recruitment process by employers (e.g., recruitment of PRO's, marketers, advertisers). Realizing that employers do a background check on individual Facebook profiles of potential candidates seeking employment in their organization, this study will be relevant and useful to such organizations and researchers particularly for employers in Nigeria and many parts of Africa.

This study proffers a better approach to collect characteristic profiles of an individual from his/her friends, family and the network of colleagues through Facebook. This, in today's world of Facebook popularity, would be a trivial task. The data would contain simple phrases/sentences that demonstrate the personality traits of an individual. As soon as such a dataset is obtained, simple association rule mining would reveal associations that are relevant and reliable for organizations as well as individuals. Once such a database of thousands of phrases/sentences is developed, through reflection specific important characteristics can be developed of all other factors which have been proven to contribute to personality traits. Additionally, such databases could be developed for different purposes and the scope of using Facebook could be variegated. Consider for example, individual behaviours on Facebook is related to one's culture, ethnicity, personal upbringing, and experiences which is demonstrated through their interactions on the Facebook platform, this can go a long way in helping the population of less technologically advanced countries make appreciable choices of individuals, for different domains and organizations.

Conclusion

The unemployment rate is high in one country than the other, and the policymakers are making unrelenting efforts to reduce the high unemployment rate. For example, Finland reduced its unemployment rate to 6% as against 6.5% in the same month of July 2019. While the developed countries are progressive in increasing their employment rate, the developed countries are still struggling to reach their employment set goals. Unlike Finland, the Nigeria unemployment rate stagnates at 23.1%. This study showcases the association rules about unemployment cases with association rule mining which belong to data mining techniques, and the result shows how to make the unemployment profile visible and the personal traits association of skillsets, online social support, and satisfaction. There is a need to consult a domain expert, for the application of the twelve association rules in this study for validation. The future researcher should work on this result and examine how to convert the association rules of unemployed Facebook users, into a database of skillsets that can easily match the job seekers with the job providers.

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Appendix I

Trait of being honest and hardworking

Conscientiousness 1: I carry out my plans

Conscientiousness 2: I pay attention to details

Conscientiousness 3: I am always prepared

Conscientiousness 4: I make plans and stick to them

Conscientiousness 5: I am exacting in my work

Openness 1: I get excited by new ideas

Openness 3: I enjoy hearing new ideas

Trait of seeking fulfillment from sources outside the self or in community

Extraversion 5: I don't mind being the center of attention

Reflects you adjusting your behavior to suit others

Agreeableness 1: I sympathize with others' feelings

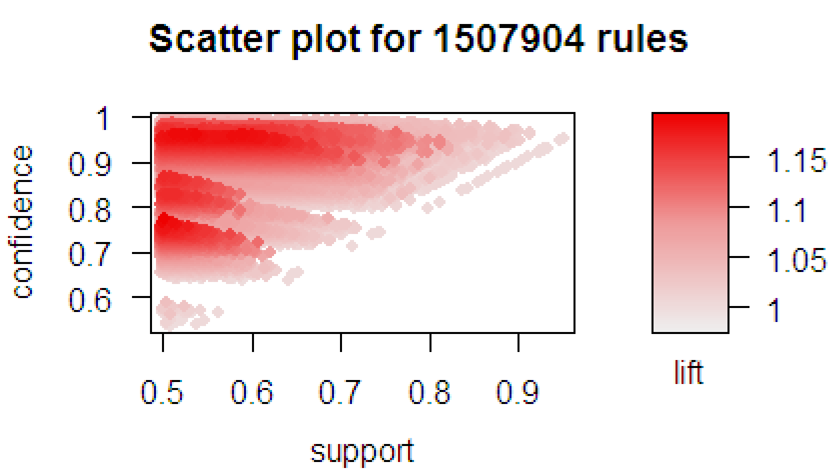
Agreeableness 2: I am concerned about others

Self-disclosure 3: I would like to use Facebook to express my personality with my friends and my friend of friends

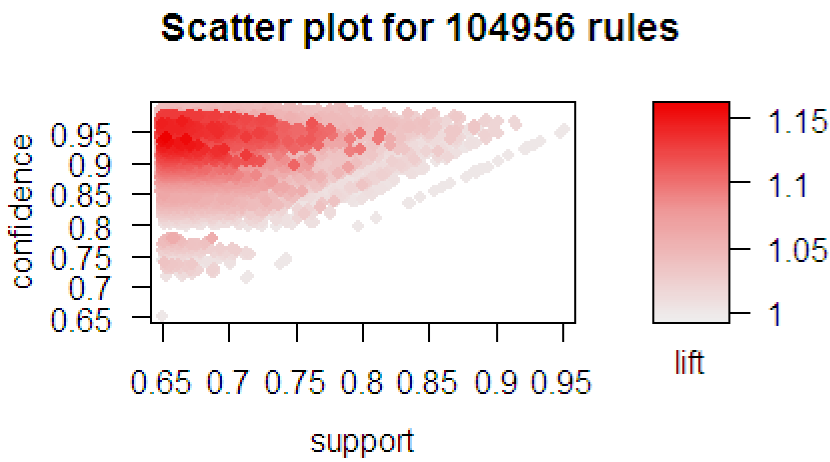
Online social support 4: I use Facebook to talk to a knowledgeable individual about job opportunities

Satisfaction 4: I will recommend people around me to use Facebook

Appendix II: Scatter plot for all the rules



Appendix III: Scatter plot for all the rules with minimum support of 0.65



Appendix IV

CON1	I carry out my plans
CON2	I pay attention to details
CON3	I am always prepared
CON4	I make plans and stick to them
CON5	I am exacting in my work
NEU1	I get stressed out easily
NEU2	I worry about bad things
NEU3	I fear for the worst things in my life
NEU4	I am filled with doubts about issues around me
NEU5	I panic easily when there is danger
AGR1	I sympathize with others' feelings
AGR2	I am concerned about others
AGR3	I respect others
AGR4	I believe that others have good intentions
AGR5	I trust what people say
OPE1	I get excited by new ideas
OPE2	I enjoy thinking about things
OPE3	I enjoy hearing new ideas
OPE4	I enjoy looking for a deeper meaning in things
OPE5	I have a vivid imagination
EXT1	I talk a lot to different people at parties
EXT2	I feel comfortable around people
EXT3	I start conversations
EXT4	I make friends easily
EXT5	I don't mind being the center of attention
OSS1	I use Facebook to gather information about job opportunities
OSS2	I use Facebook to find out things I need about job opportunities

OSS3	I use Facebook to look for information I need about job opportunities
OSS4	I use Facebook to talk to a knowledgeable individual about job opportunities
OSS5	I use Facebook to get answers to specific questions about job opportunities
SD1	I would like to use Facebook to let my life and news be known to others
SD2	I would like to use Facebook to share my unemployment experience
SD3	I would like to use Facebook to express my personality with my friends and my friend of friends
SD4	I would like to use Facebook to leave a record with photos and emoticon and show them to others
SAT1	I am satisfied with what I achieve at work
SAT2	I feel good at work
SAT3	I am satisfied with my use of Facebook
SAT4	I will keep using Facebook
SAT5	I will recommend people around me to use Facebook
CONT1	I will continue to use Facebook for my personal needs
CONT2	Using Facebook is something I would like to do to seek social support
CONT3	I see myself continuing to use Facebook for various reasons, such as getting close to others, and so on

Note: CON: Conscientiousness, NEU: Neuroticism, AGR: Agreeableness,
OPE: Openness, EXT: Extraversion, OSS: Online Social Support,
SD: Self-Disclosure, SAT: Satisfaction, CONT: Continuous Usage