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Personalized Recommendation Classification Model of Students' Social Well-being Based on Personality Trait Determinants Using Machine Learning Algorithms

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ABSTRACT

The global trend of student social well-being has steadily declined in recent years. As a result, the need for a personalized recommendation classification model that can accurately assess and identify the individual student's social well-being has become increasingly important. This article will discuss the development of an adaptive personalized recommendation classification model for students' social well-being based on personality trait determinants. Social well-being is a field that analyses society, individual behavioural patterns, behavioural networks, and cultural elements of daily life. Social well-being develops critical thinking by understanding the social frameworks that affect humans by exposing the social basis of daily actions. For instance, when students are pleased, their academic achievement, behaviour, social integration, and happiness improve. This study classifies the effects of the Big 5 Personality Traits (Extraversion, Openness, Agreeableness, Emotional Stability, and Conscientiousness) on students' Industry 4.0 Social Well-being levels by analyzing their demographic and personality traits. A dataset was gathered through a survey distributed to students in a selected institution. The classifier's accuracy was assessed using the WEKA tool on a data set of 286 occurrences and 19 traits, and a confusion matrix was constructed. After analyzing the results of all algorithms, it was determined that the IBk and Randomizable Filtered Classifier algorithms give the best accuracy on social well-being readiness, with a comparable percentage value of 91.26%. The agreeableness personality trait, which represents a person's level of pleasantness, politeness, and helpfulness, had the greatest influence on the social well-being of the students. They have a positive outlook on human behaviour and get along well with others. Since social well-being contributes to a person's increased quality of life and happiness, improving students' current quality of life would lead to the development of a social parameter that can assess the growth of a country and the increased happiness of families and communities. Personality traits models have become an increasingly important tool for understanding and predicting human behavior. By analyzing different personality trait models, we can gain insights into how accurately and reliably they can predict individual behavior. This is especially useful in fields such as psychology, marketing, and recruitment, where understanding the nuances of individual personalities can be critical to success. In this study, how different personality trait models compare in terms of accuracy and reliability is explored using different machine learning algorithms using the WEKA tool. Personality trait models are increasingly being used to measure social well-being. This model is based on the idea that individuals' personalities are composed of a set of underlying traits which can be measured and compared. By understanding these traits, we can better understand the students' social well-being and how the environment around them may impact it.

Keywords: WEKA, Personality Traits, Social Well-being, Data Mining, Classification Algorithms.

INTRODUCTION

The fourth generation of education is a learning approach that intends to educate students for the coming contemporary revolution, often known as the Industrial Revolution, also referred to as 4.0 or Industry 4.0 for short. Monitoring and aligning with new disruptive technologies requires understanding the fourth industrial revolution readiness. Industry 4.0 has caught the interest of enterprises, governments, and individuals with its innovative ideas for future computer, industrial, and social systems. During the COVID-19 outbreak, several educational institutions turned to open distance learning. This environment meets the needs of the new industrial age, which is focused on smart technology, intelligent technology, open networking, and lifelong learning. Students must be able to relate, use, and apply a wide range of content in a number of contexts. They must be guided in improving their communication skills and managing complicated situations by fostering fundamental reasoning and complex critical thinking. Students must also work using a framework of tasks through which they collaborate with their associates. However, this concept has yet to be extensively researched in scholarly articles.

Education 4.0 plays a significant role in the development of Industry Revolution 4.0's human capital. Education 4.0 incorporates a wide range of innovations, including the Internet of Things, smart technology, artificial intelligence, open connectivity, and lifelong learning. These advancements would influence the teaching and learning process and impact students' social well-being. Education 4.0 aims to develop skilled individuals who are well-versed in technological applications, particularly for communication and collaboration. The use of various technologies in teaching and learning activities can motivate students to use technology appropriately to improve academic performance. During the COVID-19 epidemic, many education institutions implemented open distance learning to resume teaching and learning.

Accordingly, institutions are becoming more concerned with their students' social well-being, where a variety of factors might influence their learning outcomes. Issues related to personality characteristics and social well-being have gained wider attention. Thus, this study used a data-driven method based on data mining techniques to assess the influence of the Big Five personality traits on the social well-being of students during the COVID-19 epidemic.

Social well-being is the overall level of health and satisfaction that an individual experiences in their lives. It is heavily influenced by the physical, psychological, and social factors that affect the individual (Tuzovic & Kabadayi, 2021). It is important to understand the determinants of social well-being to develop personalized strategies to improve students' lives. Personality traits are the psychological characteristics of an individual which can influence their social well-being (Anglim et al., 2020). It is important to identify and understand the personality traits of students in order to develop personalized strategies to improve their social well-being.

Personality refers to psychological characteristics that contribute to a person's persistent and distinctive patterns of feeling, thinking, and behaving (Cervone & Pervin, 2018; Jani & Han, 2015). Personalities can be defined by the Big Five personality traits (agreeableness, conscientiousness, extraversion, neuroticism, and openness), which differ between character segmentation (Razavi, 2020). Big data mining in education is similar to data mining in social networking but with the incorporation of Personality Classification Opportunities and research. Education contributes to the classification or categorization of factors in huge data sets in terms of the success and failure of students and educational systems in context (Uddin & Lee, 2016). Teachers in higher education could use knowledge discovery skills and access to big data and data mining techniques to identify trends in the teaching and learning process (Drayton-Brooks et al., 2020). Self-concealment is a personality trait characterized by persons who suppress personal and confidential information, hence impeding catharsis and well-being. Davis's (2001, as cited in Magsamen-Conrad et al., 2014) model of pathological Internet usage was used as the framework for this study also to include communication technologies and investigate the problem in the context of information-management-related personas. To understand how these constructs relate to and impact one another, it is vital to have a fundamental grasp of communication technology addiction, self-concealment, online social capital, and well-being (Magsamen-Conrad et al., 2014). Although consumers' technology connection may improve their well-being, it still might be detrimental to their long-term well-being. For instance, excessive technological dependency among children has been shown to cause undeveloped social and motor skills (Hollebeek & Belk, 2021; Simendinger & Stibe, 2016). Davis (2001, as cited in Magsamen-Conrad et al., 2014) showed how technology addiction and social networking capital might function as intervening factors in the negative well-being implications of self-concealment, particularly through the development of bridging social capital. In contrast to previous research that has concentrated on the often negative impact of technology addiction in the context of personality factors, this study focuses on the positive impact of technology instead. Davis (2001, as cited in Magsamen-Conrad et al., 2014) identified a situation where technology dependence may be beneficial. It is important to examine the different effects of digital well-being and explore methods to future-proof these concepts so that they do not serve as 'foot-in-the-door' technology (Widdicks, 2020).

Identification technology can be a disruptive technology in today's education sector. Through social science research, the influence of social, economic, demographic, political, ecological, and technological factors on well-being can be examined (Robeyns, 2020). Hence, this study applied data mining techniques to measure the effect of Big Five Personality Traits on the social well-being of students using classification techniques to understand how personality traits affect social well-being levels in the educational context. This study leads to the development of a unique personality trait model that incorporates elements of the Big Five personality traits and social well-being to help employers assess potential employees and help individuals better understand themselves. Creating a digital platform that provides in-depth analysis of individuals' personality traits and social well-being that can be used by employers, job seekers, and individuals alike will therefore be critical to ensuring that the level of professionalism and productivity of employees is always top-notch.

RELATED WORKS

This section will discuss various personality traits and data mining in the education field and other related research areas. The worldwide economic impact of enabling technologies is measured by productivity, employment, and unemployment, as well as technical or legal changes. Digitalization is the integration and digitalization of digital technology into everyday life (Doost Mohammadian & Rezaie, 2020). It would have a significant impact on the social-economic environment, particularly employment (Sima et al., 2020).

Emerging technologies can help in the creation of these significant consumer mythologies, rituals, and experiences (Rose, 2014, as cited in Hollebeek & Belk, 2021), thus affecting their well-being. Hollebeek and Belk's (2021) study concentrated primarily on the influence of bridging social capital and suggested that future research into the impact of bonding capital on technology addiction. Digital wellness solutions should, for example, assist users in disengaging from their devices, concentrating on social encounters with friends, family members, and colleagues, and reducing social disruptions caused by technology (Widdicks, 2020).

Student social well-being is a complex concept encompassing various components of life, such as physical and mental health, learning, relationships, and overall quality of life. It is essential to consider all these aspects to provide students with the best possible advice and interventions (Lavy, 2020). The development of a personalized recommendation classification model of students' social well-being, based on personality trait determinants, can be a powerful tool in helping to improve the efficacy of student interventions. Recent research in the area of student social well-being has identified various factors that contribute to social well-being, including personality traits, family structure, and social networks (Salehi et al., 2017). Personality traits can provide insight into how an individual interacts with their environment and can be used to identify potential areas for intervention. For example, individuals with higher levels of extroversion may be more likely to engage in social activities, while those with higher levels of neuroticism may be more likely to experience negative emotions and thoughts (Gubler et al., 2021). It is also important to consider family structure, as it can influence an individual's ability to form relationships and gain access to resources (Middlemiss et al., 2019). Furthermore, social networks can provide students with support and guidance.

The core question guiding this study explores students' Big Five personality traits regarding social well-being. The current challenges and understanding related to the higher education environment, such as disruption in education, human resource quality, and the use of recent technology in learning, will be analyzed to identify the choice of strategy to deal with technology disruption (Sudirwan & Pelawi, 2019). Some research suggests that the variances in the adoption of different Industry 4.0 technologies are related to projected benefits for the product, operations, and elements of negative effects in emerging economies (Sima et al., 2020).

Personality trait models are an important tool for understanding and predicting the behavior of individuals (Bleidorn & Hopwood, 2019). They are used in many fields, such as psychology, marketing and recruitment. The main components of a personality traits model include self-report measures, observational measures, physiological measures, and cognitive measures (Pekruna, 2020). Self-report measures assess individuals' beliefs about themselves and their behavior (Fazio et al., 2021). Observational measures assess how people interact with one another in different contexts (Clarke et al., 2021). Physiological measures measure changes in the body, such as heart rate or respiration rate, that can indicate emotional states or reactions to stimuli (Jerath & Beveridge, 2020). Cognitive measures measure the ability to think logically or to solve problems. All four components work together to provide a comprehensive view of an individual's personality traits which can be used to inform decisions about them or predict their future behavior.

Personality traits models are used to measure social well-being by assessing the individual's psychological characteristics, such as their values, beliefs, attitudes and behaviors (Kim & Kim, 2020). These models can be used to identify the strengths and weaknesses of an individual's personality traits and how these traits affect their ability to interact with others. They can also be used to identify potential areas of improvement in an individual's social well-being. Additionally, personality trait models can help organizations understand their workforce better and make more informed decisions about recruitment, training and development programs (Van den Broek et al., 2021).

Personality trait models are used by organizations to understand the behavior and preferences of their customers. These models help them to better predict customer needs, develop strategies, and create personalized experiences. There are different types of personality trait models available, each with its own unique strengths and weaknesses. The most common types include the Big Five Model, the Myers-Briggs Type Indicator (MBTI), and the Enneagram model (Radisavljević et al., 2022). The Big Five Model categorizes people into five personality types: extroverted, introverted, open-minded, conscientiousness and agreeableness (Hadziahmetovic & Mujezinovic, 2021). The Myers-Briggs Type Indicator categorizes people into four categories: intuitive (N), sensing (S), thinking (T) and feeling (F), with each category containing four similar traits (Amirhosseini & Kazemian, 2020). The Enneagram model categorizes people as nine different types of personalities, with each type having a single defining trait (Abdelhamid et al., 2023). Each personality classification has its own strengths and weaknesses; for example, those who are extroverts may have an easier time making. Each of these models has been developed to measure different aspects of human personalities, such as values, attitudes, motivations, and behaviors. In addition to these models, there are also other more specialized personality trait models such as the HEXACO model or the NEO-PI-R model (Ashton & Lee, 2020). Mairesse et al. (2007) and Wang and Chen (2020) trained classification algorithms to recognize all Big Five personality traits in their respondents' conversations and written material. According to Cobb-Clark and Schurer (2012) and Utami et al. (2021), the Big Five personality traits are consistent over time because the techniques used to measure the Big Five model are consistent; therefore, the data may be used at any time. The Big Five Personality Model was used in their study because it is the widely used technique for predicting a person's personality traits based on tests and a review of the literature. Shankhdhar et al. (2020) studied the relationship between several personality traits of students and used classification to assess the personality traits and effectiveness of students in choosing career options based on their personality traits, interests, and capacity to enter a course and top programs per locality and fee structure. Another study investigated how the digital welfare community designed instruments that might accidentally reduce the negative effects of technology (Widdicks, 2020), considering how people often know what technology can and can never accomplish and how their objectives, behaviour, and decisions are affected (Anderson & Rainie, 2018).

The five elements of Big Five Personality Traits are summarised below (Goldberg, 1981, 1990; Costa and McCrae, 1992; John & Srivastava, 1999, as cited in Zaidi et al., 2013):

1) Extraversion – warmth, gregariousness, assertiveness, activity, a desire for excitement, and pleasant emotions. Certain interruptions are caused by technology. However, properly handled creativity increases the overall standard of lifestyle
2) Openness – fantasy, aesthetics, feelings, actions, ideas, values
3) Agreeableness – trust, straightforwardness, altruism, compliance, modesty, tender-mindedness
4) Emotional Stability (Neuroticism) – anxiety, anger hostility, depression, self-consciousness, impulsiveness, vulnerability
5) Conscientiousness – competence, order, dutifulness, achievement, striving, self-discipline, deliberation

Furthermore, the five Social Well-being elements adapted from Keyes (1998, as cited in Demong et al., 2021) in the current model are listed below:

1) Social Integration - Social Integration (having a sense of belonging to a community) is an experience of social connectedness that provides comfort and support.
2) Social Acceptance - Social Acceptance (accepting others as they are) refers to having a good attitude toward others while recognizing and accepting individual differences.
3) Social Contribution - Social Contribution (a desire to contribute to society) is referred to as social contribution. It is the belief that one’s reality is valuable to society and that the outcomes of one’s efforts are respected or appreciated by others.
4) Social Actualisation - Social Actualisation (positive solace level with society) is the concept that persons, communities, and social orders could evolve or develop decisively.
5) Social Coherence - Social coherence (perceiving the social environment as unsurprisingly feasible) relates to public interest or activity, a sense that society and culture are clear, to some extent, legitimate, predictable, and meaningful.

Overall, technology produces some interruptions. However, if well-managed, innovation increases the general quality of life by providing several benefits, such as improved access to information and culture, producing an inverted “U-form” that will present the entire benefits of communication via digital innovation (Anderson & Rainie, 2018).

Humans can and should take the initiative to adapt to changes brought upon by digital technology.

The major goal of Educational Data Mining (EDM) is to find valuable patterns and knowledge from student data and to use them for the benefit of the education community. EDM aims to extract patterns in an education database from which information may be discovered and used to make educational system decisions (Ismail et al., 2013). This emerging topic of importance involves the development of systems for discovering information from educational contexts (Parmar et al., 2015). EDM and learning analytics (LA) are two distinct disciplines that describe and use data mining in higher education and other educational contexts to extract significant knowledge and patterns from academic databases (Aldowah et al., 2019). Thus, this study adopted the personality traits as determinants that affect the social well-being readiness level of students in higher learning institutions and classified the hidden patterns of data using data mining techniques. High levels of agreeableness, conscientiousness, extraversion, and openness are connected to higher levels of happiness, while high levels of neuroticism are linked to lower levels of happiness. Social well-being is described as a community's ability to fulfill the population's basic human needs, lay the groundwork for individuals and groups to enhance and preserve their well-being, and create an environment in which all people may overcome obstacles (Bakar et al., 2016). Yu et al. (2021) revealed that five personality traits are strongly connected to total social well-being, with social support serving as a mediator in the interactions between the five personality traits. Joshanloo, Rastergar and Bakhshi (2012) found that neuroticism is adversely connected to social acceptance, social contribution, and social coherence among the Big Five personality traits, while conscientiousness is linked to social involvement in a good way. The findings suggest that social well-being and personality traits, as explained using the Big Five personality traits, would affect the social well-being of students and society in general.

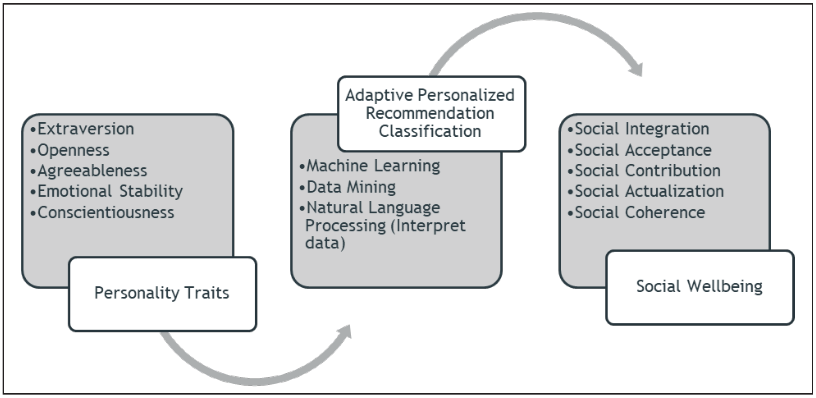
Model Development

In recent years, the development of technology has led to the introduction of applications that can recommend activities for well-being, such as exercise and mindfulness. However, these applications are often limited to popular activities which lack personalization and do not consider the user's character. As a result, students may not find the activities that are most suitable for them. To address this issue, we present a personalized recommendation system that uses machine learning algorithms to adapt to the student's personality traits, as depicted in Figure 1. Our platform is based on an architecture that considers the user's character to select the most suitable classification based on machine learning results. To ensure that the recommendations are beneficial for the user, we provide explanations to persuade students and improve their engagement.

Our platform uses natural language processing and sentiment analysis to analyze the user's responses to the questionnaire and calculate the user's personality traits. The user's character is then matched with the activities that are most suitable for them. Furthermore, we use reinforcement learning to identify the activities that the user is most likely to be interested in and recommend those activities to the user.
We also provide visualizations of the user's progress along with explanations of the reasons behind the recommendations. This encourages the user to take action and increase their engagement with the activities. Moreover, our platform allows users to provide feedback on the activities they have completed, which helps us continuously improve the recommendations. In summary, the personalized recommendation system provides tailored suggestions based on the student's personality tratis to ensure that the activities are most suitable for the user. The visualizations and explanations help increase user engagement and reinforce the suggested activities. We believe this model can contribute to best practices for well-being and provide an effective solution to the current lack of personalization in existing recommending applications. The goal of this article is to develop a personalized recommendation classification model of students' social well-being, based on personality traits determinants as shown in Figure 1. This model would enable educators and counselors to more accurately identify and address the individual needs of students. The model would take into account personality traits in order to provide an assessment of a student's social well-being.

Figure 1

Personalized Recommendation Classification Model of Students' Social Well-being based on Personality Traits Determinants



METHODOLOGY

The adaptive personalized recommendation classification model is a model that takes into account the individual personality traits of the student in order to develop an accurate assessment of their social well-being. The model is developed using a combination of data mining, machine learning, and natural language processing techniques. Data mining techniques are used to identify the personality traits of the student. This information is then used to develop a personalized recommendation classification model. The model is based on the individual's personality traits and is designed to identify the social well-being of the student.

Machine learning techniques are used to analyze the data and develop a personalized social well-being recommendation classification model. The model is then used to generate a personalized recommendation classification for the student. Natural language processing techniques are used to interpret the data and create a comprehensive assessment of the student's social well-being. The model is then used to provide personalized social well-being recommendations for the student. The first step in the development of the recommendation classification model is to collect data on the various factors that influence social well-being. This data can be collected through questionnaires and surveys. Once the data is collected, the next step is to apply machine learning algorithms to the data in order to identify patterns and correlations. The output of the machine learning algorithms can then be used to generate personalized recommendations for each student. The WEKA tool is an effective classification tool for this study's objectives. WEKA implements the majority of the algorithms used in machine learning and displays the outcomes (Villavicencio et al., 2021). It uses several common machine-learning graphical links, unifies various pre-treatment and after-processing procedures, applies many distinct research algorithms to data sets, and evaluates the outcome (Zhong, 2011). Three algorithms that have been selected for this study are listed below:

Instances-Based k (IBk)

Instance-based learning is a non-parametric (no prior model assumptions) which works only for real-valued inputs and does not need a training phase of K Nearest Neighbour (KNN) that stores all the available cases on a similarity measure. In machine learning, instance-based learning (also known as memory-based learning) refers to a class of learning algorithms that, rather than conducting explicit generalization, compare new problem cases with examples encountered in training that have been kept in memory. Simple instance-based learner with the class of the nearest k training instances as the test instance class was utilized. The 'k' in KNN is a parameter that refers to the number of nearest neighbours to include in the majority of the voting process. In general, choosing the value of k is k= square root (N), where N stands for the number of samples in the training dataset. In this case, N= 286. Equation 1 refers to where the instances are described by n attributes.

$$(x, y) = -\sqrt{\sum_{i=1}^{n} f(x_i, y_i)} \tag{1}$$

We define $f(x_{i,}y_i) = (x_i - y_i)^2$ for numeric-valued attributes and $f(x_{i,}y_i) = (x_i \neq y_i)^2$ for Boolean and symbolic-valued attributes. IBk is identical to the nearest neighbour algorithm except that it normalizes its attribute ranges, process instances incrementally, and has a simple policy for tolerating missing values.

Randomizable Filtered Classifier

This technique trains k distinct binary classifiers to categorize k various classes, including one that separates a specific class from the others. Samples from one class are regarded as good examples, whereas samples from the other classifications are labeled as negative examples. This approach identifies the appropriate class of a sample by using the greatest result for an unknown sample. Technique for building binary classifiers based on N different binary classifiers as depicted in Equation 2. For the $\imath$th classifier, let the positive examples be all the points in class i, and let the negative examples be all the points not in class i. Let f_i be the $\imath$th classifier. It classifies using:

$$f(x) = \arg\max f_i(x) \tag{2}$$

KStar (K*)

As demonstrated in Equation 3, the KStar or K* method is an optimization technique for determining the shortest routes between a given pair in a particular pointed node. This approach employs an instance-based classifier that uses the K Nearest Neighbour (KNN) method, which is comparable to IBk, with the goal of dividing n data points into k clusters. K* employs an entropic distance metric based on the likelihood of changing one occurrence into another. The use of entropy is critical for an instance distant, and information theory aids in calculating the distance between instances. As a result, entropic distance is utilized to find the most comparable occurrences in a data collection. New data points, n, are attached to the most expected class, y_i, where i=1…k. The K* equation is computed as follows:

$$K^*(y_i, n) = -InP^*(y_i, n) \tag{3}$$

P* represents the chance of x reaching y via a random path. It provides a consistent technique for dealing with real-valued characteristics, individuals can express, and null values. One of the limitations of this algorithm is it takes a long time to train. The likelihood of each category is calculated. The estimated relative probabilities approximated the category dispersion at the occurrence space point.

Most other procedures yielded a single category as a consequence of categorization. For ease of comparison, the class with the highest likelihood was selected as the categorization of the new event. The possibilities are to choose a class at random using relative probabilities or to provide the outcome as a normalization probability distribution.

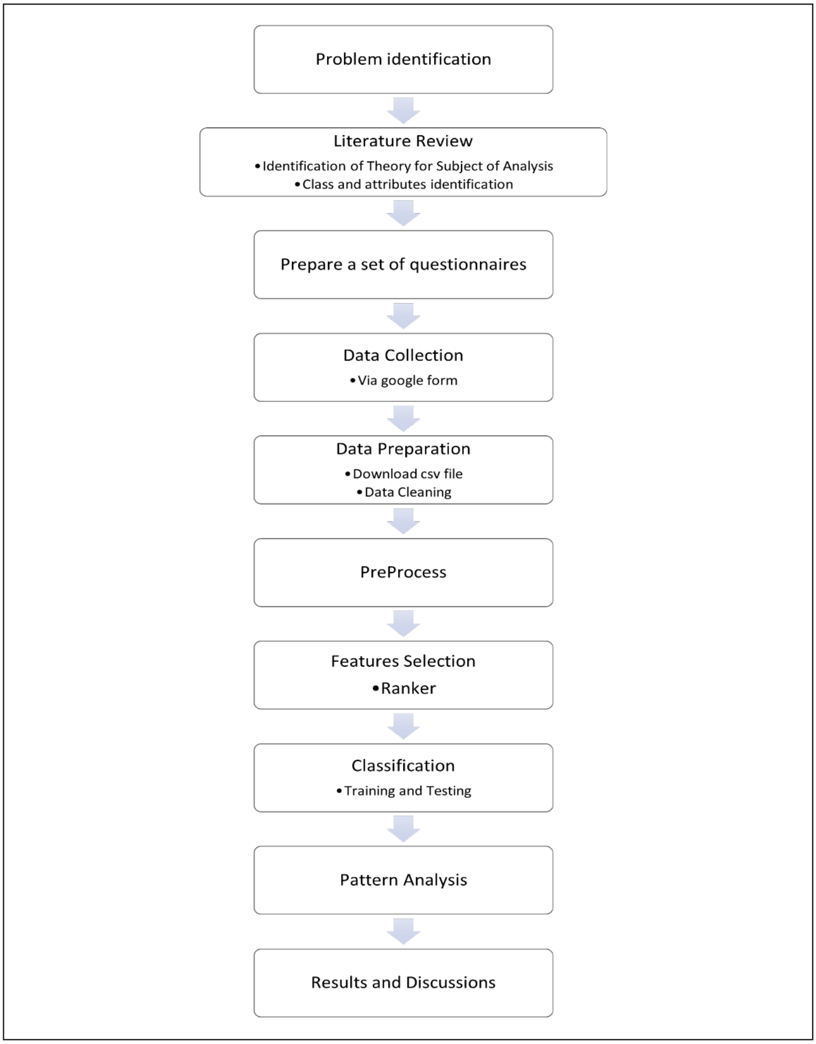
Data mining is the process of collecting meaningful knowledge from vast amounts of data. Data mining technology was applied to an unstructured information system to investigate technology performance patterns and digital educational engagement technology related to computer teaching evaluation. It focused on categorization and prediction to identify students with poor learning performance (Francis & Babu, 2019). Based on their Big-Five personality characteristics, individuals were divided into several unique segments using the K-means clustering technique (Razavi, 2020). WEKA can implement several algorithms for a dataset. It incorporates most machine learning methods and is able to visualize the results. The WEKA Explorer and WEKA Experimenter interfaces were used to evaluate the reliability utilizing the training group validation option.

Data mining was used in this study. Figure 1 depicts the data analysis conducted on the gathered dataset. Before using the algorithm, pre-processing techniques such as the normalize method, the replacing missing value technique, and the attribute selection approach were used. Normalization was performed to equalize the frequency value from 0 to 1. Missing values were replaced to alter the blank data to the average data of the attributes, followed by the attribute selection approach, which ranked the attributes to identify the highest contributing factors.

As shown in Figure 2, the dataset contains the demographic profiles and their Big Five personality traits criteria that were collected using a questionnaire. The dataset contains 286 instances and 19 attributes. No missing values were found in the dataset. The data was collected using an online survey (Google Form) and converted to a CSV file and later to an ARFF file using WEKA (Experimenter).

Figure 2

Methodology



Data pre-processing was done to refine the data through 'data cleaning' and filtering. Then, using the 'Ranker' search method, the feature selection functions ranked the highest contributing factors to the subject of analysis, which is students' social well-being based on the five personality traits and also demographic data profiles. The 'Use Training Set' Classification and focus on Result attributes were applied to predict the target class in the dataset that assigns items in a collection by classes performed and classification algorithms with the highest accuracy that fit the model. Training and testing functions for all related classifiers were selected, and the three highest accuracy models representing the model were selected for results and findings. Next, the pattern analysis used an attribute plot matrix to visualize the patterns of the selected attributes.

EXPERIMENT

Six simple algorithms are used to forecast the Big Five Personality Traits that influence students' social well-being. Figure 1 depicts the suggested framework. Six classifiers were created during the training phase, and classifications were made during the testing phase.

Data Processing Phase

The data for this study was gathered from a selected university in Klang Valley, Malaysia. Initially, data of seventy-two attributes was divided into three sections: Section A: Demographic profiles, with nine attributes; Section B: Big Five Personality Traits, with forty-four attributes then grouped into five main categories of dimensions; and Section C: Social Well-being, with nineteen attributes then grouped into five main dimensions. Finally, nineteen demographic attributes, five Big Five personality traits attributes, and five Social Well-being attributes were selected following the data cleaning process. Table 1 displays the features chosen as well as their potential values.

Table 1

Dataset Descriptions

Attribute	Description	Data Type and Values
Gender	The gender of the respondents	Nominal: Male; Female
Age	Age of the respondents	Nominal: 19-22; 23-26; 27-30; Above 31
Field of Study	Field of study of the respondents	Nominal: Social Science; Science and Technology
Mode of Study	Mode of study of the respondents	Nominal: Part-time; Full-time
Level of Study	Level of study of the respondents	Nominal: Diploma; Bachelor; Master
Working?	Do the respondents work?	Nominal: Yes; No
Amount of monthly income	The monthly income of the respondent	Nominal: Below RM2000; RM2001-RM4000; RM4001-RM6000; RM6001-RM8000; Above RM8001
If working, your position	Position of the respondents if working	Nominal: Low-level management; Middle-level management; Top-level management
Employment sector	The employment sector of the respondents	Nominal: Public; Private; Own
Extraversion	Extraversion of Big Five Personality Traits (BFPT) total marks of each respondent	Numerical (Likert Scale-1-5): 8 attributes; Minimum = 8; Maximum=40
Agreeableness	Agreeableness of BFPT total marks of each respondent	Numerical (Likert Scale-1-5): 9 attributes; Minimum = 9; Maximum=45
Conscientiousness	Conscientiousness of BFPT total marks of each respondent	Numerical (Likert Scale-1-5): 9 attributes; Minimum = 9; Maximum=45
Neuroticism	Neuroticism of BFPT total marks of each respondent	Numerical (Likert Scale-1-5): 8 attributes; Minimum = 8; Maximum=40
Openness	Openness of BFPT total marks of each respondent	Numerical (Likert Scale-1-5): 10 attributes; Minimum = 10; Maximum=50

(continued)

Attribute	Description	Data Type and Values
Social Integration	Social Integration of Social Well-being level of measurements	Nominal (Likert Scale-1-5): 1=Strongly Disagree; 2=Disagree; 3=Neutral; 4=Agree; 5=Strongly Agree
Social Acceptance	Social Acceptance of Social Well-being level of measurements	Nominal (Likert Scale-1-5): 1=Strongly Disagree; 2=Disagree; 3=Neutral; 4=Agree; 5=Strongly Agree
Social Contribution	Social Contribution of Social Well-being level of measurements	Nominal (Likert Scale-1-5): 1=Strongly Disagree; 2=Disagree; 3=Neutral; 4=Agree; 5=Strongly Agree
Social Actualization	Social Actualisation of Social Well-being level of measurements	Nominal (Likert Scale-1-5): 1=Strongly Disagree; 2=Disagree; 3=Neutral; 4=Agree; 5=Strongly Agree
Social Coherence	Social Coherence of Social Well-being level of measurements	Nominal (Likert Scale-1-5): 1=Strongly Disagree; 2=Disagree; 3=Neutral; 4=Agree; 5=Strongly Agree

ANALYSIS AND RESULTS

Feature Selection

The feature selection algorithm in WEKA determines the most significant qualities by employing correlation-based attribute assessment, as illustrated in Table 2 and Table 3. From the result, it can be summarized that the most influential attribute contributing to the social well-being element is conscientiousness (Attribute No. 3). This finding is similar to the findings by Utami et al. (2021), which showed that the conscientiousness trait explaining the responsible, diligent, and organized nature. Furthermore, Razavi (2020) also found that conscientiousness positively correlates with most mobile usage and time spent on social media. Search Methods using Ranker with CorrelationAttributeEval have been applied to all five elements of Big Five Personality Traits as the dimensions that affect each element of social well-being.

Table 2 shows the summary of feature selection methods using Ranker as the search method and InfoGainAttributeEval as the attribute evaluator. The highest contributing factor toward social well-being readiness elements is the conscientiousness personality trait, while the least contributing factor is openness.

Table 2

Summary of Attribute Selection Using Feature Selection Methods- Info Gain Attribute Evaluation Method

	Social Well-being Elements				
Ranking	Social Integration	Social Acceptance	Social Contribution	Social Actualization	Social Coherence
1	Conscientiousness	Extraversion	Conscientiousness	Conscientiousness	Neuroticism
2	Openness	Agreeableness	Neuroticism	Neuroticism	Conscientiousness
3	Agreeableness	Neuroticism	Agreeableness	Agreeableness	Extraversion
4	Extraversion	Conscientiousness	Extraversion	Extraversion	Agreeableness
5	Neuroticism	Openness	Openness	Openness	Openness

Table 3

Attribute Selection using feature selection methods-InfoGainAttribute Evaluation Method

Attribute Evaluator (supervised, Class (nominal): 6 **Social Integration**): Correlation Ranking Filter Ranked attributes: 0.1369 3 Conscientiousness 0.1102 5 Openness 0.0977 2 Agreeableness 0.0977 1 Extraversion 0.0948 4 Neuroticism Selected attributes: 3,5,2,1,4 : 5
Attribute Evaluator (supervised, Class (nominal): 6 **Social Acceptance**): Correlation Ranking Filter Ranked attributes: 0.1383 1 Extraversion 0.1004 2 Agreeableness 0.0766 4 Neuroticism 0.0625 3 Conscientiousness 0.0505 5 Openness Selected attributes: 1,2,4,3,5 : 5
Attribute Evaluator (supervised, Class (nominal): 6 **Social Contribution**): Correlation Ranking Filter Ranked attributes: 0.1447 3 Conscientiousness 0.1118 4 Neuroticism 0.1085 2 Agreeableness 0.0975 1 Extraversion 0.094 5 Openness Selected attributes: 3,4,2,1,5 : 5
Attribute Evaluator (supervised, Class (nominal): 6 **Social Actualisation**): Correlation Ranking Filter Ranked attributes: 0.1832 3 Conscientiousness 0.1376 4 Neuroticism 0.1145 2 Agreeableness 0.1012 1 Extraversion 0.0496 5 Openness Selected attributes: 3,4,2,1,5 : 5

```
Attribute Evaluator (supervised, Class (nominal): 6 Social Coherence):
        Correlation Ranking Filter
Ranked attributes:
 0.1396  4 Neuroticism
 0.136   3 Conscientiousness
 0.1343  1 Extraversion
 0.1227  2 Agreeableness
 0.0468  5 Openness
Selected attributes: 4,3,1,2,5 : 5
```

Specifying the Selected Algorithms

Classification algorithms include Decision Tree, Neural Network, Naïve Bayes, K-Nearest neighbour, Random Forest, AdaBoost, and Support Vector Machines (Sudirwan & Pelawi, 2019). In this study, knowledge structures available in the WEKA software were employed to mine the dataset. The accuracy of the classifier was assessed by using the WEKA tool on the dataset. On the Weka interface, the effects of Big Five Personality Traits on the social well-being level dataset were classified with the three sets of classification algorithms, namely lazy, meta and trees, resulting in more than 80 per cent precision. The performance of these six algorithms methods was assessed using the data testing training mode.

Classification Algorithm Selection

After testing and training the dataset with all active machine learning algorithms in WEKA, three main groups of machine learning algorithms appeared to work best with this dataset. The three main groups were a lazy group with IBk (Instances-Based k) and KStar algorithms, a meta group with RandomCommittee and RandomizedableFilteredClassifier algorithms, and a trees group using RandomForest and RandomTree algorithms. Since the class of this study is in nominal data type, the function group will not be analyzed because it uses regression analysis, which requires numerical data type class values. Based on the findings, the accuracy of the selected classifier developed varies from 87.41% to 91.26%, which could be enhanced by selecting relevant characteristics. The WEKA software was used to select the most significant qualities. The training data testing mode was performed to assess the performance of these six algorithms in the dataset. After evaluating the results of all algorithms, the greatest accuracy with a comparable percentage was found through the IBk and RandomizeableFilteredClassifier methods, as shown in

Table 4 and Figure 3, respectively. These results are similar to a study by Nunsina et al. (2020), where the K-Nearest Neighbor method's accuracy value was 93.83%.

Table 4

Evaluation of Different Classifiers Based on Correctly and Incorrectly Classified Instances Accuracy

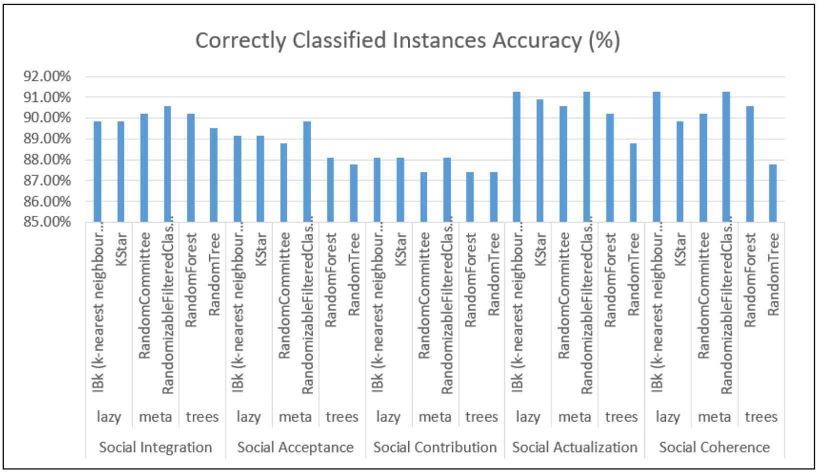
Social Well-being Element	Classification Group	Classification Algorithm	Accuracy	Correctly Classified Instances	Incorrectly Classified Instances
Social Integration	lazy	IBk (k-nearest neighbour algorithm)	89.86%	257	29
		KStar	89.86%	257	29
	meta	RandomCommittee	90.21%	258	28
		Randomizable Filtered Classifier	90.56%	259	27
	trees	RandomForest	90.21%	258	28
		RandomTree	89.51%	256	30
Social Acceptance	lazy	IBk	89.16%	255	31
		KStar	89.16%	255	31
	meta	RandomCommittee	88.81%	254	32
		Randomizable Filtered Classifier	89.86%	257	29
	trees	RandomForest	88.11%	252	34
		RandomTree	87.76%	251	35

(continued)

Social Well-being Element	Classification Group	Classification Algorithm	Accuracy	Correctly Classified Instances	Incorrectly Classified Instances
Social Contribution	lazy	IBk (k-nearest neighbour algorithm)	88.11%	252	34
		KStar	88.11%	252	34
	meta	RandomCommittee	87.41%	250	36
		Randomizable Filtered Classifier	88.11%	252	34
	trees	RandomForest	87.41%	250	36
		RandomTree	87.41%	250	36
Social Actualization	lazy	IBk (k-nearest neighbour algorithm)	91.26%	261	25
		KStar	90.91%	260	26
	meta	RandomCommittee	90.56%	259	27
		Randomizable Filtered Classifier	91.26%	261	25
	trees	RandomForest	90.21%	258	28
		RandomTree	88.81%	254	32
Social Coherence	lazy	IBk (k-nearest neighbour algorithm)	91.26%	261	25
		KStar	89.86%	257	29
	meta	RandomCommittee	90.21%	258	28
		Randomizable Filtered Classifier	91.26%	261	25
	trees	RandomForest	90.56%	259	27
		RandomTree	87.76%	251	35

Figure 3

Classification Accuracy of Correctly Classified Instances Percentage for Selected Algorithms



Association Rules Results

Association rules were employed to discover the common if/then patterns. The main connections were determined by utilizing characteristics of support and trust. There were two elements to the association rule. They are a history (if a portion) and hence (then part). The most often used method for correlation-based data collection is the Apriori algorithm (Nafie & Hamed, 2018). The study used WEKA and the Apriori method on the datasets. The reason for using the Apriori Algorithm was to find the association rules that have minimum support equal to 0.1 (10%) and minimum confidence equal to 0.9 (90%). The minimum support to 0.1 was adjusted to produce a more frequent item collection. Setting a minimum support of 0.2 or higher could eliminate many attributes, but the minimum number of attributes would be insufficient to make a reasonable choice. However, a minimum confidence of 0.9 can be set higher because this limit might provide fewer rules. Based on the results, the lowest support was 0.1(10%) (29 cases), the metric (confidence) minimum was 0.9 (90%) and 18 cycles. As indicated in Table 5, the optimal rules were identified. The default setting for the number of best rules for the Apriori algorithm was ten, and the results showed that social coherence dominated with the highest number of best rules generated, equal to ten rules.

Table 5

Association Rules Using Apriori as One of the Popular Association Rule Mining Algorithms for Frequent Pattern Mining

Social Integration

Minimum support: 0.1 (29 instances)

Minimum metric <confidence>: 0.9

Number of cycles performed: 18

Best rules found: **4 rules generated**

1. **Agreeableness**=High Neuroticism=Low 37 ==> Conscientiousness=High 36 <conf:(0.97)> lift:(2.38) lev:(0.07) [20] conv:(10.93)
2. Neuroticism=Low 43 ==> Conscientiousness=High 41 <conf:(0.95)> lift:(2.33) lev:(0.08) [23] conv:(8.47)
3. **Agreeableness**=Medium Neuroticism=Medium Social Integration=Agree 40 ==> Extraversion=Medium 37 <conf:(0.93)> lift:(1.44) lev:(0.04) [11] conv:(3.57)
4. Conscientiousness=High Neuroticism=Medium Social Integration=Agree 36 ==> Extraversion=Medium 33 <conf:(0.92)> lift:(1.42) lev:(0.03) [9] conv:(3.21)

Social integration is dominated by Agreeableness of Big Five Personality Traits with two rules out of four rules generated.

Social Acceptance

Minimum support: 0.1 (29 instances)

Minimum metric <confidence>: 0.9

Number of cycles performed: 18

Best rules found**: 4 rules generated**

1. **Agreeableness**=High Neuroticism=Low 37 ==> Conscientiousness=High 36 <conf:(0.97)> lift:(2.38) lev:(0.07) [20] conv:(10.93)
2. Neuroticism=Low 43 ==> Conscientiousness=High 41 <conf:(0.95)> lift:(2.33) lev:(0.08) [23] conv:(8.47)
3. Conscientiousness=Medium Neuroticism=Medium Openness=Medium Social Acceptance=Neutral 34 ==> Extraversion=Medium 32 <conf:(0.94)> lift:(1.46) lev:(0.04) [10] conv:(4.04)
4. Conscientiousness=Medium Neuroticism=Medium Social Acceptance=Neutral 41 ==> Extraversion=Medium 37 <conf:(0.9)> lift:(1.4) lev:(0.04) [10] conv:(2.92)

Social acceptance is dominated by the conscientiousness of Big Five Personality Traits with two rules out of four rules generated.

Social Contribution
Minimum support: 0.1 (29 instances)
Minimum metric <confidence>: 0.9
Number of cycles performed: 18
Best rules found: **5 rules generated**
1. **Agreeableness**=High Neuroticism=Low 37 ==> Conscientiousness=High 36 <conf:(0.97)> lift:(2.38) lev:(0.07) [20] conv:(10.93)
2. Neuroticism=Low 43 ==> Conscientiousness=High 41 <conf:(0.95)> lift:(2.33) lev:(0.08) [23] conv:(8.47)
3. **Agreeableness**=Medium Conscientiousness=Medium Neuroticism=Medium Social Contribution=Neutral 37 ==> Extraversion=Medium 34 <conf:(0.92)> lift:(1.43) lev:(0.04) [10] conv:(3.3)
4. **Agreeableness**=Medium Neuroticism=Medium Social Contribution=Neutral 49 ==> Extraversion=Medium 45 <conf:(0.92)> lift:(1.43) lev:(0.05) [13] conv:(3.5)
5. **Agreeableness**=Medium Conscientiousness=Medium Neuroticism=Medium Openness=Medium Social Contribution=Neutral 32 ==> Extraversion=Medium 29 <conf:(0.91)> lift:(1.41) lev:(0.03) [8] conv:(2.85)

For social contribution, agreeableness dominated the Big Five Personality Traits with four rules out of five rules generated.

Social Actualization
Minimum support: 0.1 (29 instances)
Minimum metric <confidence>: 0.9
Number of cycles performed: 18
Best rules found: **8 rules generated**

1. **Agreeableness**=High Neuroticism=Low 37 ==> Conscientiousness=High 36 <conf:(0.97)> lift:(2.38) lev:(0.07) [20] conv:(10.93)
2. Neuroticism=Low 43 ==> Conscientiousness=High 41 <conf:(0.95)> lift:(2.33) lev:(0.08) [23] conv:(8.47)
3. Extraversion=Medium Agreeableness=Medium Openness=Medium Social Actualisation=Neutral 32 ==> Conscientiousness=Medium 30 <conf:(0.94)> lift:(1.72) lev:(0.04) [12] conv:(4.85)
4. Conscientiousness=Medium Neuroticism=Medium Openness=Medium Social Actualisation=Neutral 37 ==> Extraversion=Medium 34 <conf:(0.92)> lift:(1.43) lev:(0.04) [10] conv:(3.3)
5. Extraversion=Medium Agreeableness=Medium Social Actualisation=Agree 46 ==> Neuroticism=Medium 42 <conf:(0.91)> lift:(1.55) lev:(0.05) [14] conv:(3.76)
6. **Agreeableness**=Medium Openness=Medium Social Actualisation=Neutral 46 ==> Conscientiousness=Medium 42 <conf:(0.91)> lift:(1.67) lev:(0.06) [16] conv:(4.18)
7. Neuroticism=Medium Openness=Medium Social Actualisation=Neutral 44 ==> Extraversion=Medium 40 <conf:(0.91)> lift:(1.41) lev:(0.04) [11] conv:(3.14)
8. Conscientiousness=Medium Neuroticism=Medium Social Actualisation=Neutral 42 ==> Extraversion=Medium 38 <conf:(0.9)> lift:(1.41) lev:(0.04) [10] conv:(3)

For social actualization, agreeableness, conscientiousness, extraversion, and neuroticism of the Big Five Personality Traits contributed two rules for each trait to generate eight rules. The openness trait did not contribute to social actualization and no rules were generated.

Social Coherence
Minimum support: 0.1 (29 instances)
Minimum metric <confidence>: 0.9
Number of cycles performed: 18
Best rules found: **10 rules generated**
1. **Agreeableness**=High Neuroticism=Low 37 ==> Conscientiousness=High 36 <conf:(0.97)> lift:(2.38) lev:(0.07) [20] conv:(10.93)
2. Neuroticism=Low 43 ==> Conscientiousness=High 41 <conf:(0.95)> lift:(2.33) lev:(0.08) [23] conv:(8.47)
3. Conscientiousness=Medium Neuroticism=Medium Openness=Medium Social Coherence=Neutral 35 ==> Extraversion=Medium 33 <conf:(0.94)> lift:(1.47) lev:(0.04) [10] conv:(4.16)
4. **Agreeableness**=Medium Conscientiousness=Medium Social Coherence=Neutral 33 ==> Openness=Medium 31 <conf:(0.94)> lift:(1.49) lev:(0.04) [10] conv:(4.08)
5. Extraversion=Medium Agreeableness=Medium Openness=Medium Social Coherence=Neutral 31 ==> Neuroticism=Medium 29 <conf:(0.94)> lift:(1.58) lev:(0.04) [10] conv:(4.23)
6. Neuroticism=Medium Openness=Medium Social Coherence=Neutral 43 ==> Extraversion=Medium 40 <conf:(0.93)> lift:(1.45) lev:(0.04) [12] conv:(3.83)
7. **Agreeableness**=Medium Neuroticism=Medium Social Coherence=Neutral 42 ==> Extraversion=Medium 39 <conf:(0.93)> lift:(1.44) lev:(0.04) [11] conv:(3.74)
8. Extraversion=Medium Agreeableness=Medium Social Coherence=Neutral 42 ==> Neuroticism=Medium 39 <conf:(0.93)> lift:(1.57) lev:(0.05) [14] conv:(4.3)
9. Extraversion=Medium Conscientiousness=Medium Social Coherence=Neutral 41 ==> Openness=Medium 38 <conf:(0.93)> lift:(1.47) lev:(0.04) [12] conv:(3.8)
10. Extraversion=Medium Conscientiousness=Medium Neuroticism=Medium Social Coherence=Neutral 36 ==> Openness=Medium 33 <conf:(0.92)> lift:(1.46) lev:(0.04) [10] conv:(3.34)

For social coherence, it is dominated by extraversion of Big Five Personality Traits with four rules out of five rules generated.

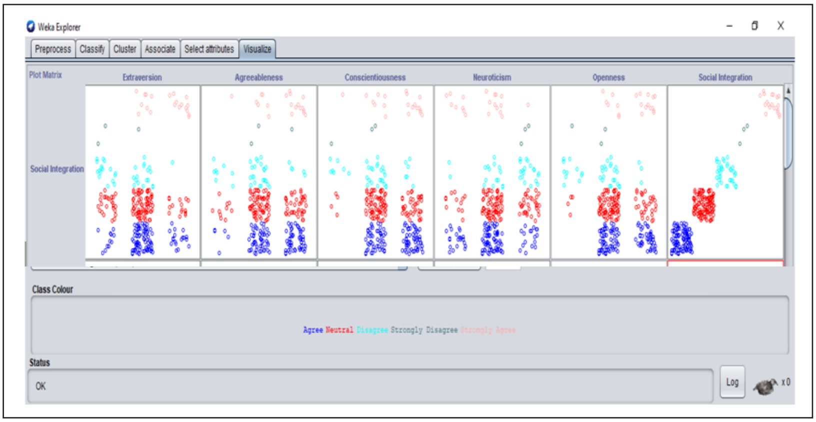
Overall, agreeableness dominated the Big Five Personality Traits, affecting more towards the social well-being of students' learning during the COVID-19 pandemic as shown in Table 5. This finding is similar to the findings by Wang and Chen (2020) and Razavi (2020).

Visualization for Trend Analysis

Figure 4 to 8 show the trends of agreement of Big Five Personality traits towards social well-being elements based on the dataset.

Figure 4

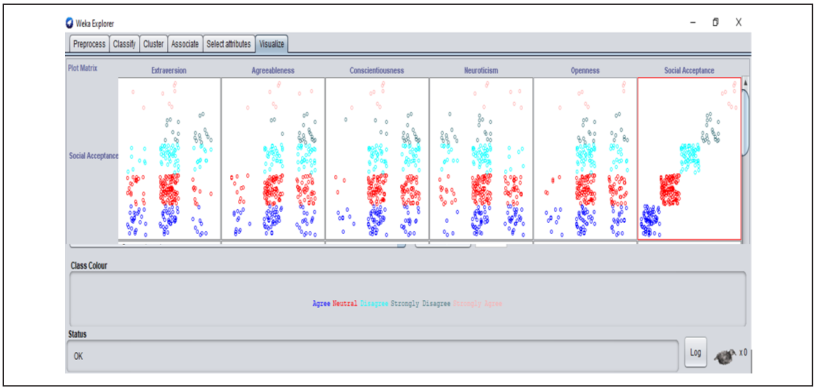
Big Five Personality Traits Trends of Social Integration



As shown in Figure 4, the results are dominated by Neutral and Agree levels of agreement for all the five elements of the personality traits for social integration. The results on social integration could suggest that the students in the selected institution have a sense of belonging to a community during the online teaching and learning sessions held during the COVID-19 pandemic. The students could have also gotten good support from the stakeholders regarding the teaching and learning process. This result is also supported by Magsamen-Conrad et al. (2014), who reported that the increased time spent online increased social interaction and integration.

Figure 5

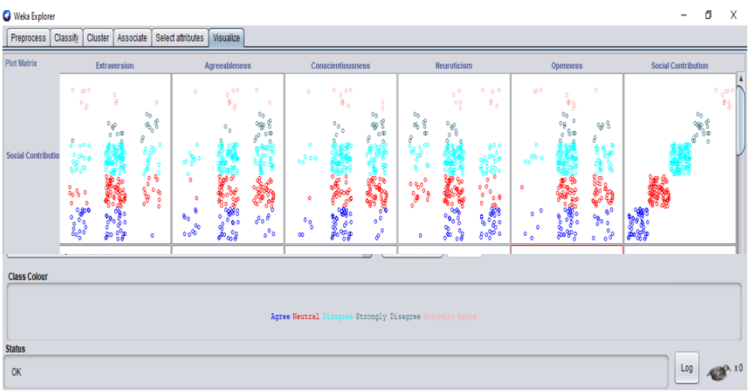
Big Five Personality Traits Trends of Social Acceptance



As shown in Figure 5, the observed amount of agreement for all five personality factors for social acceptance is dominated by neutral and agreed levels. This result suggests that the students have a favourable attitude towards others and that the online sessions recognize and accept individual diversity. In other words, the students willingly accepted their colleagues' strengths and weaknesses during the teaching and learning process. Social assistance has been shown to help alleviate stress and its repercussions (Hansen et al., 2020).

Figure 6

Big Five Personality Traits Trends of Social Contribution



As shown in Figure 6, the degree of consensus for all five social contribution components is driven by the level of neutrality and disagreement. This result demonstrates that there is no willingness to contribute to society among the students. This is probably because the government had restricted social events during the pandemic due to health and security reasons. Similar findings were also reported by Swartz (2020) and Martinex-Dominguez and Fierros-Gonzalez (2021).

Figure 7

Big Five Personality Traits Trends of Social Actualisation

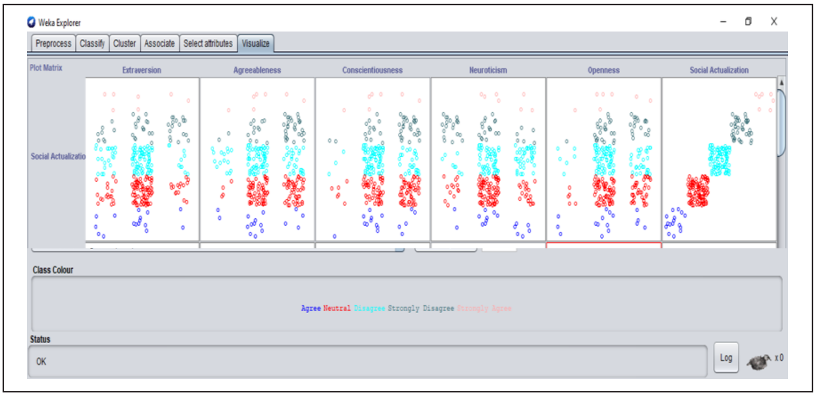
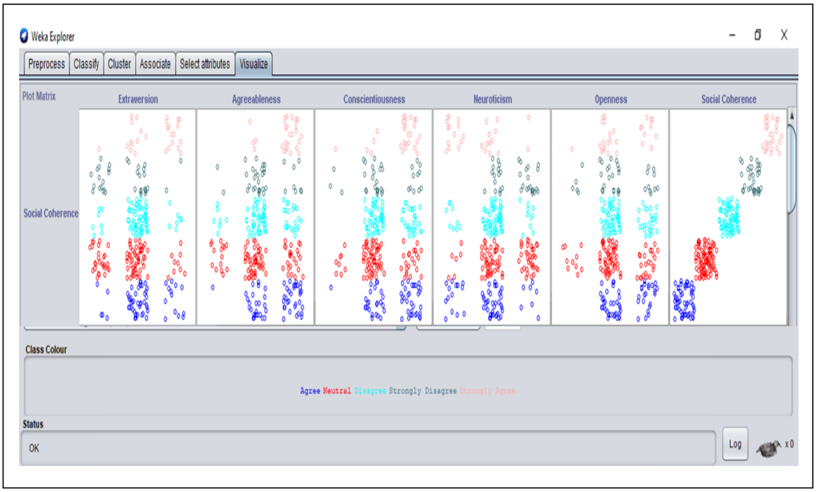


Figure 7 shows that neutrality and disagreement are driving the degree of consensus for all five components of social actualization. This shows that the level of decisive conduct in the online teaching and learning sessions was low. A probable reason might be that the students had to cope with different restrictions from various authorities throughout the online teaching and learning process.

Figure 8

Big Five Personality Traits Trends of Social Coherence



As shown in Figure 8, the level of consensus for all five components of social cohesion is determined by neutrality and disagreement. This result could be due to the COVID-19 pandemic, which caused the degree of social attention to be low. During this period, the students were not able to hold or attend social activities. The sense of the quality and operation of the social environment is referred to as social coherence, and it indicates that a society is meaningful. However, little research has been done on the impact of social coherence on social well-being.

DISCUSSION

The modern world has become increasingly focused on well-being and health, with an ever-growing number of health and wellness applications designed to track individuals' progress and help them maintain good physical and mental health. However, what is often overlooked is that personality traits can also play an important role in an individual's life satisfaction and overall well-being. Personality traits are the unique qualities that make up a person's character, such as their level of extroversion, conscientiousness, agreeableness, and emotional stability. These traits can significantly impact how individuals perceive and interact with the world around them. For example, more extroverted individuals may be better able to cope with stress due to their tendency to seek support and stimulation from others, while those who are more emotionally stable may be better able to regulate their emotions and maintain a sense of calm in difficult situations.

With the increasing demand for health and wellness applications, there is a need for personalized recommendations that consider different student's personality traits. This is especially true when it comes to mental health applications, as different personalities may respond differently to the same strategies and prompts. For example, an application that encourages students to take part in self-care activities such as journaling or meditation may be more successful for those who are more introverted, while those who are more extroverted may benefit from activities such as networking or group activities.

Furthermore, personality traits can also be used to identify warning signs for certain mental health issues, such as anxiety or depression.

For example, those who are more emotionally unstable may be more likely to experience episodes of anxiety or depression, while those who are more open-minded may be more likely to seek out help and support. In conclusion, it is clear that personality traits can play an important role in a student's life satisfaction and overall well-being. Therefore, it is important to consider these traits when developing health and wellness applications to provide personalized recommendations that meet the needs of different students. This study provides valuable insight into how students with different personality traits should handle their social well-being environment. The results revealed that all five personality traits were significantly related to overall social well-being elements, with the accuracy of classification algorithms between 87% and 92% of correctly classified instances. High levels of agreeableness, conscientiousness, extraversion, and openness were connected to higher levels of happiness, while high levels of neuroticism were linked to lower levels of happiness. The results also affirm the importance of social well-being in improving academic performance and mental health in tertiary-level education.
The highest contributing personality traits that affect the social well-being of students in higher learning institutions were conscientiousness, followed by neuroticism, agreeableness, extraversion, and openness, respectively. Conscientiousness dominated the social integration, social contribution, and social actualization of the social well-being elements. On the other hand, social acceptance is dominated by extraversion and social coherence is controlled by neuroticism. A high degree of conscientiousness leads to good social well-being elements. Community is an important aspect of students' daily activities.

The diverse types of personality traits will influence their response to the social environment, which may cause different levels of social well-being. Students with different personality traits may build their social relations in different ways. Therefore, they need to know the level of their social well-being environment to create a safe environment for the learning process and to excel in their academic performance. The results might be different if the dataset is divided into different clustering based on the demographic of the respondents, such as field of study and mode of study. Thus, for future research, the data collection and analysis should be expanded to different data mining techniques and different operations, such as clustering or database segmentation.

Many researchers use personality assessments for different purposes. However, the current methods are not very satisfying because they do not provide a sufficiently in-depth understanding of a student's personality for their social well-being in achieving academic performance. Students and institutions alike would benefit from more detailed information about the potential students' personalities and how those personalities affect their ability to perform in the academic field. This study incorporates both data from personality assessment methods and data on social well-being, which institutions can use to make fair assessments of potential hires or individuals to better understand themselves. This study collects data from both specific questionnaires on the personality traits of candidates and social well-being data that helps indicate how a person performs in the institution. The information is collected anonymously and contains no identifying information about the user without their consent.

CONCLUSION AND FUTURE WORKS

This study examined the forecast accuracy of the students' social well-being level using various categorization algorithms derived from IBk and KStar algorithms from the lazy group, RandomizedableFilteredClassifier and RandomCommittee algorithms from the meta group, and RandomForest and RandomTree algorithms from the trees group. The experimental findings demonstrated that the qualities selected from the initial dataset are extremely important and that it was sufficient for the unknown classes to increase their predictive accuracy. The Randomizedable Filtered Classifier algorithm has been shown to be a stronger classification model with 91.26% accuracy on correctly categorized data using the model data when compared to the other models. This approach would assist institutions in anticipating students' social well-being and issues influencing subjective well-being. The default option was 10 for the Apriori algorithm, and the findings indicate that the largest number of the best rules created, equivalent to 10, are dominated by social cohesion. The Randomizable Filtered Classifier surpassed the other classifiers based on accuracy and classifier errors. The Apriori method was also used to determine the best rules for association rule mining among all the characteristics, and the best rules were shown. When coupled with other data mining approaches, developing classification algorithms in this manner assists in constructing more efficient classification tools.

The algorithm's accuracy could be improved in future development. The data might be expanded to capture more of the students' personality traits and digital abilities and mined using different classification algorithms to estimate the level of social well-being for future work. The authors are also interested in working on data on students' social well-being for different modes of study in the future to determine which method of study has the most impact on social well-being characteristics. Enabling speculative concepts and continuous discussions are vital for reducing the negative effects of technology today and developing the digital well-being of the community in the future. All present and potential effects of digital well-being technology should be explored. Personality traits models are becoming increasingly popular to measure the well-being of humans in different fields. However, with the rise of many models and tools, ethical considerations need to be taken into account when using them. These considerations, include privacy, accuracy, and fairness that can be researched in the future to measure how it impacts the readiness of respondents in giving their inputs and response to this study.

Privacy is an important factor to consider when using a personality traits model. It is essential to ensure that user data is kept secure and protected from any unauthorized access or use. Accuracy is also a key factor in determining how effective a personality traits model can be in generating content that accurately reflects the user's personality and preferences. Lastly, fairness should also be taken into account when using a personality trait model, as it should not discriminate against any particular group of people or individuals based on their race, gender, or other characteristics.

The adaptive personalized recommendation classification model is a powerful tool for assessing and improving the social well-being of students. The model takes into account the individual's personality traits and uses data mining, machine learning, and natural language processing techniques to develop an accurate assessment of the student's social well-being. This model can be used to develop personalized strategies to improve the social well-being of individual students.

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