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ENHANCING PERSONALITY CHARACTERISTICS ANALYSIS WITH SMOTE AND ASSOCIATION RULE MINING: A CASE STUDY ON INTROVERTS AND EXTROVERTS

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Abstract. *The classification of personality characteristics, typically divided into introverts and extroverts, differs from general public characteristics. Personality variation within teams significantly impacts team development and presents challenges for leaders in effective team management. Understanding how personality characteristics align with different types of work can enhance team potential. This research identifies variables relevant to analyzing co-worker personalities within organizations. An association rules model was constructed using questionnaire data to analyze introverted and extroverted characteristics. Imbalances in the data distribution were addressed using the synthetic minority oversampling technique, resulting in a balanced dataset with 3,198 extroverts and 3,512 introverts. The Apriori algorithm then generated association rules from this dataset, focusing on single-dimensional rules with high accuracy for each class. For the introvert class, the highest accuracy (96.52%) was associated with "Q81A: I am quiet around strangers (Agree)", while the extrovert class achieved 68.81% accuracy with "Q82A: I do not talk a lot (Disagree)". Optimal accuracy with two-rule associations reached 98.49% for introverts and 80.48% for extroverts.*

Keywords: Apriori algorithm, Association rule mining, Imbalanced data, Introvert and extrovert, Personality characteristics, SMOTE method

1. Introduction.

Introversion and extroversion are fundamental concepts in psychological theories of human personality, introduced by Jung, Carl Gustav [1], a psychiatrist and psychologist from Germany. These core personality characteristics are further delineated within the Myers-Briggs Type Indicator (MBTI) framework, which enables analysis of habits, identities, strengths, weaknesses, information processing tendencies, thought patterns, and decision-making approaches related to each individual [2]. The MBTI model categorizes personality characteristics across four key dimensions: Extraversion (E) versus Introversion (I), Sensing (S) versus Intuition (N), Thinking (T) versus Feeling (F), and

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Judging (J) versus Perceiving (P) [3]. Research into personality typologies is crucial, as divergent personality attributes profoundly influence how individuals engage and collaborate in various contexts. The motivation for this research stems from the role of teamwork in driving organizational advancement and progress [2,3].

For example, Gonzalez-Torre et al. [4] focused on selecting suitable astronauts for space missions using the K-means clustering algorithm. Their study applied the IPIP-120 personality assessment tool to evaluating participant personalities. K-means clustering helped identify natural groupings within a team, an essential factor for selecting individuals with complementary personality traits. The findings identified two distinct personality groups among the simulated astronauts, underscoring that selecting a team for long-term space missions involves not only recognizing individual personality traits but also considering compatibility within the team. The K-means clustering algorithm provided an effective approach for analyzing personality data from large groups, thereby enhancing the strength and depth of personality assessments.

A comprehensive understanding of the characteristics associated with each personality type enhances adaptation in various contexts, including collaborative work. Recognizing behavioral patterns helps individuals identify their strengths and weaknesses. In teamwork, understanding personality types supports appreciation of differences among members [5]. For example, Moradi et al. [6] studied responses to work disruptions among introverted and extroverted team members. They found that, while some members exhibited shyness and spoke less, they still contributed positively by energizing the team through alternative methods. Introverted individuals often produced detailed technical work and excelled in tasks requiring concentration. Conversely, characteristics like strong leadership and high self-confidence, often associated with extroversion, could make team members feel less inclined to share openly. When individuals adapt to collaborate by leveraging their own personality characteristics, they establish boundaries in their work and foster a cooperative framework that encourages teamwork.

Identifying suitable personality types for specific work environments enhances work efficiency. Understanding personality characteristics helps individuals find appropriate career paths and guides refinement in organizational structures. For example, Itani et al. [7] analyzed motivating factors related to extroverted and introverted customer personality traits and their engagement with restaurants. The study examined both direct and indirect effects of these personality types on customer engagement, a crucial factor for favorable business outcomes. Indicators such as the correlation matrix, descriptive statistics, and average variance provided insights for restructuring business models to emphasize individual customer personality traits. Additionally, Zulfiqar et al. [8] investigated the negative impact of social media usage on employee performance, with personality traits serving as moderating factors. Integrating cognitive theory and Eysenck's theory of personality, the study examined whether excessive social media use reduces cognitive performance. Results revealed that extroverted individuals were most distracted by social media, while ambiverts, who exhibit both extroverted and introverted characteristics, experienced the least distraction. Digital well-being applications were used to assess addictive behaviors related to social media usage, offering insights into managing its effects in the workplace.

Based on a review of studies on personality characteristics, this research aims to explore individual personality characteristics that enhance team collaboration. The focus is on identifying relationships between features associated with introverted and extroverted personality types, as these unique characteristics often require adaptations to collaborate effectively in task-specific ways. The objective is to improve accuracy in identifying feature associations, leading to more precise classification results. Once features that accurately classify introvert and extrovert outcomes are identified, the model derived from association rules can be applied to adapting work contexts to the specific characteristics of team members. For example, Vishnubhotla and Mendes [9] examined the association between personality traits and team climate in Agile teams within a telecommunications company. Data collected from Sweden and India via a web-based survey were analyzed through correlation and regression analyses. The findings indicated a significant negative relationship between neuroticism and team climate, suggesting that high levels of neuroticism may impact collaboration due to emotional responses. Regression analysis identified key personality traits influencing team climate overall.

Additionally, Kucukozer-Cavdar and Taskaya-Temizel [10] analyzed the impact of personality traits on online group work among students. Using the Ten Item Personality Inventory (TIPI), undergraduate students unfamiliar with one another were assigned to small online groups based on personality traits through learning management system forums. The study demonstrated that factors such as gender and academic background influenced the success of online groups, using data mining techniques.

Each personality type has unique strengths and areas for improvement. Understanding and adapting to these characteristics can help build strong teams. This concept led to the analysis of features derived from questions in the introvert-extrovert personality test to identify characteristics associated with each type [11,12]. Other research has analyzed association rules to determine which features best distinguish personality characteristics. For example, Huda and Chowanda [13] investigated personality detection using data from Twitter in Indonesia. The study predicted user personality traits by analyzing tweets, applying machine learning algorithms such as Support Vector Machine, Naïve Bayes, Decision Tree, and K-Nearest Neighbor. Each model was evaluated using cross-validation and F1-score metrics, with Naïve Bayes showing the highest effectiveness.

Collaborative teamwork often generates a broader range of perspectives than individual work, as integrating diverse viewpoints enhances understanding. Qualitative analysis of teams with varied personality types suggests that encouraging behaviors associated with these characteristics strengthens diversity and balance in team interactions [14].

The contribution of this research is an analysis of personality characteristics as follows.

- This study explores the association between personality dimensions, focusing on introversion and extroversion. Classification as either introverted or extroverted is based on lifestyle patterns, activities, and sources of energy.
- This research utilized data from questionnaires based on an introvert-extrovert personality test, where respondents selected answers that best reflected their characteristics. Responses were analyzed to determine alignment with introversion or extroversion.
- An association rule model was used to examine the personalities of team members, focusing on single-dimensional features extracted through the Apriori algorithm. The performance of the model was evaluated based on confidence and accuracy metrics.

This research is organized as follows. Section 2 presents related work, while Sections 3 and 4 provide details on the research methodology and experimental results, respectively. The conclusion is discussed in Section 5.

2. Related Work.

2.1. Introvert and extrovert personality characteristics. Introverts and extroverts represent two contrasting personality types, each with distinct characteristics that influence how individuals interact with their surroundings. Introverts tend to prioritize introspection, focusing on emotions, thoughts, and personal feelings over social interactions. Solitude provides comfort for many introverts, who often display strengths such as strong memory retention, problem-solving skills, and proactive planning abilities, all contributing to enhanced cognitive performance in various intellectual tasks [1,15]. In contrast, extroverts thrive in social settings, enjoying activities that allow self-expression among peers. They are typically competitive, achievement-oriented, and energized by social interactions. Extroverts may feel lonely or unstimulated when alone, experiencing a greater sense of well-being when surrounded by friends or in large gatherings.

2.2. **Apriori algorithm.** The Apriori algorithm was used to extract association rules from transaction data. This algorithm identifies frequent itemsets, which are groups of items that commonly appear together in transactions and uses these to construct association rules [16,17]. A key parameter, the minimum support value, sets a threshold for itemset frequency. Itemsets meeting or exceeding this threshold qualify as frequent itemsets and are subsequently used to build association rules [18].

2.3. **Synthetic Minority Oversampling Technique (SMOTE).** SMOTE is a widely used method for addressing imbalanced data [19]. It increases the representation of the minority class to create a more balanced dataset, achieving equal or nearly equal sizes for majority and minority classes through oversampling. Rather than relying on simple replication, SMOTE generates new data points from the existing minority class, which improves data distribution. Additionally, SMOTE helps retain essential data, enhancing the quality of analysis and model performance [20,21].

3. **Methodology.** This research aims to identify interrelated features indicative of personality characteristics. The methodology involves creating association rules between features to determine those yielding the most accurate classification results. Specifically, this study examines relationships between characteristics identified through the introvert-extrovert personality test, which assesses personality traits, including external behavioral responses. Each question in the test represents one feature, with result classes categorized as introvert or extrovert based on collected data.

The Apriori algorithm is applied for feature selection, identifying features associated with personality expressions. The algorithm generates association rules and selects features with the highest accuracy values for each class, examining associations among features to identify those indicative of introvert or extrovert traits. Data preparation for this research facilitates association mining, following principles from applied machine learning. This preparatory step is essential for effective data analysis, involving multiple stages tailored to the model.

The flowchart of the proposed method is shown in Figure 1. The dataset processing included the following steps: 1) data preparation, 2) missing values detection, and 3) correlation analysis. In summary, the process of creating association rule models follows

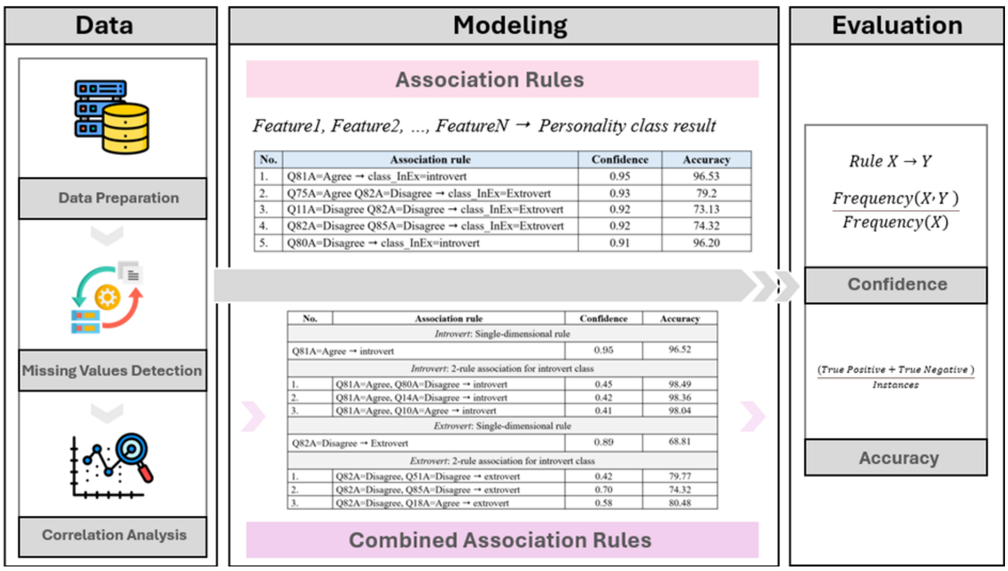

FIGURE 1. The flowchart of the proposed method

principles of the applied machine learning process, with each step adapted for effective model creation. These steps include data preparation, following the Knowledge Discovery in Databases (KDD) framework for thorough examination and cleaning. The next steps involve building the association rule model, selecting relevant features, and evaluating model performance. The detailed steps are outlined below.

3.1. **Data preparation.** Data preparation involves selecting and organizing datasets for analysis to create association rules. This process ensures the dataset is appropriately structured for use in the association rules model. Certain datasets have unique characteristics that are essential for effective analysis. The process begins by preparing the dataset according to applied machine learning principles, including feature identification, data transformation, and cleaning. The specific steps for data preparation are outlined below.

3.1.1. *Dataset selection.* The dataset used in this experiment is publicly accessible and contains data from personality tests assessing introvert and extrovert characteristics. This dataset includes 7,188 instances, with 91 questions serving as features for identifying personality types, and two output classes: introvert and extrovert. The introvert-extrovert personality test is divided into three parts: Part A, Part I, and Part E. For this research, only data from Part A was utilized. Part A consists of 91 questions aimed at determining personality characteristics, specifically identifying individuals as introvert or extrovert. Responses to each question are rated on a 5-level scale: 1 = Disagree, 2 = Slightly disagree, 3 = Neutral, 4 = Slightly agree, and 5 = Agree. In the final section of the questionnaire, respondents were asked for consent to use their data for research; only responses from those who consented were included in the dataset.

3.1.2. *Data transformation.* After examining the dataset, the next step is to transform the data into a format suitable for creating association rule models. This involves converting response level values, originally represented by numerical scores (1, 2, 3, 4, and 5), into their corresponding meanings, such as 1 for "disagree" and 2 for "slightly disagree". Additionally, the class attribute is transformed, with 1 representing the introvert class and 2 representing the extrovert class.

3.2. **Missing values detection.** The analysis included identifying anomalies and detecting missing values in the dataset, followed by essential data cleaning. This process, a critical and time-intensive step, involved detecting data redundancy, removing missing values, and correcting outliers. The dataset was cleaned by removing features irrelevant to modeling association rules. Unrelated features, such as gender, native English, and age, as well as content from Parts I and E, were excluded. Starting with an original dataset containing 281 features, data cleaning reduced it to 91 relevant features and one class attribute.

3.3. **Correlation analysis.** This process examines interrelated features and the direction of their associations with both personality classes. It includes analyzing feature creation for a more in-depth understanding. In this research, correlation analysis is integrated with the imbalanced data process, which is detailed in the following sections.

3.3.1. *Imbalanced data.* This research uses a dataset of 5,394 rows from an introvert-extrovert personality test, applying the hold-out cross-validation method to developing a machine learning process using a training set to create an association rules model. An imbalance in class distribution is evident, with 3,512 rows in the introvert class and 803 rows in the extrovert class, necessitating data balancing adjustments. Balancing the dataset is essential to minimize prediction bias and improve the accuracy of association rule analysis in identifying personality characteristics.

To achieve balance, the SMOTE was used to enhance the extrovert class, the minority with 803 instances, by generating new data based on the original dataset. This process improved the distribution of the extrovert class, making it more comparable to the introvert class, which is the majority. After applying SMOTE, the extrovert class increased to 3,198 instances, resulting in a total of 6,710 instances in the balanced dataset. This adjustment ensures sufficient data to create robust association rules.

3.3.2. *Building an association rules model.* To build the association model, the Apriori algorithm is applied to generating association rules based on result classes that indicate introvert or extrovert characteristics. This process involves generating association rules with result classes positioned on the Left-Hand Side (LHS) in the association rule format [5], as follows: *Feature1, Feature2, . . . , FeatureN* $\rightarrow$ *Personality Class Result.*

Building association rules using the Apriori algorithm involves setting specific support and confidence values. In this research, different support and confidence levels were tested to identify the most suitable values for an effective association rule model, as shown in Table 1.

Table 1. Setting the support and confidence values for the creation of association rules

Time	Support value	Confidence value	Number of association rules	Number of rules associated with introvert and extrovert classes
#1	0.9	0.9	0	0
#2	0.9	0.85	0	0
#3	0.85	0.8	0	0
#4	0.85	0.75	0	0
#5	0.8	0.7	0	0
#6	0.75	0.6	0	0
#7	0.5	0.3	0	0
#8	0.4	0.3	0	0
#9	**0.3**	**0.25**	**342**	**144**
#10	0.27	0.2	1306	211
#11	0.2	0.1	> 4000	> 1000

Based on Table 1, a support value of 0.3 and a confidence value of 0.25 were selected. Only association rules with the result class on the Right-Hand Side (RHS) were retained, yielding a total of 144 rules. Analysis across 11 rounds of parameter-setting experiments showed that higher support and confidence values did not produce enough association rules.

The analysis began with a support value of 0.3 and a confidence value of 0.25 (iteration #9). These parameters were chosen for building the association rule model, as they generated an adequate number of rules for further analysis. Although alternative parameter settings could yield more association rules and potentially include additional relevant features, the lower support and confidence values from experiment #9 were deemed optimal for this study.

3.4. **Measurement of the effectiveness of association rules.** To identify an appropriate association rule model for analyzing features related to the occurrence of the result class, it is essential to establish performance metrics for the rules. This evaluation is divided into two parts: the structure of the association rules and the parameters used to measure rule effectiveness [22].

3.4.1. *Support value.* The support value measures the effectiveness of each feature, serving as an initial filter to exclude less frequent rules. Features are selected only if their values exceed the specified minimum support threshold. If a feature appears infrequently, making it insufficient to form a meaningful association with other features, the rule associated with that feature is excluded from further consideration.

3.4.2. *Confidence value.* The confidence value is a parameter in the association rule creation process that identifies frequently occurring features. This value filters association rules, selecting only those that meet the minimum confidence threshold [23]. Rules with high confidence values are more reliable for accurately representing feature associations, thereby effectively characterizing personality characteristics.

4. **Experimental Results.**

4.1. **Data association rules using the Apriori algorithm.**

The creation of association rules involves selecting rules that reach the minimum support value of 0.3 and the minimum confidence value of 0.25, resulting in a total of 144 rules. This research emphasizes single-dimensional association rules to identify relevant features for analyzing personality characteristics, specifically focusing on rules derived from a single feature. These association rules are divided into introvert and extrovert result classes, as shown in Table 2. Typically, association rule models prioritize rules involving associations among multiple features.

Table 2. Association rules generated using the Apriori algorithm

No.	Association rule	Confidence	Accuracy
1	Q81A = Agree → class_InEx = introvert	**0.95**	**96.52%**
2	Q75A = Agree Q82A = Disagree → class_InEx = Extrovert	0.93	79.2%
3	Q11A = Disagree Q82A = Disagree → class_InEx = Extrovert	0.92	73.13%
4	Q82A = Disagree Q85A = Disagree → class_InEx = Extrovert	0.92	74.32%
5	Q80A = Disagree → class_InEx = introvert	0.91	96.20%

As shown in Table 2, which presents sample association rules, single-dimensional rules (e.g., Rules 1 and 5) demonstrate higher accuracy than those resulting from multi-feature associations. Additionally, the single-dimensional features do not exhibit associations with other features based on various association rules, as observed in the table.

This research proposes a new association rule model by combining individual features to examine associations that differentiate the result classes as introvert and extrovert, and to assess the accuracy values generated by these feature combinations, as shown in Tables 3 and 4. The creation of association rules is divided into two types: those where features are combined to form associations that define result classes (introvert or extrovert). In evaluating features for identifying personality characteristics, each feature appears to function independently, without continuous associations with others. Therefore, single-dimensional features were selected for experimentation to develop this new association rule model.

Table 3. Association rules of single-dimensional personality characteristics feature of introvert class

No.	Association rule	Confidence	Accuracy
1	Q81A = Agree → class_InEx = introvert	**0.95**	**96.52%**
2	Q80A = Disagree → class_InEx = introvert	0.91	96.20%
3	Q14A = Disagree → class_InEx = introvert	0.88	95.36%
4	Q10A = Agree → class_InEx = introvert	0.87	93.55%
5	Q19A = Disagree → class_InEx = introvert	0.84	92.81%

TABLE 4. Association rules of single-dimensional personality characteristics feature of extrovert class

No.	Association rule	Confidence	Accuracy
1	Q82A = Disagree → class_InEx = Extrovert	**0.89**	**68.81%**
2	Q51A = Disagree → class_InEx = Extrovert	0.75	40.38%
3	Q85A = Disagree → class_InEx = Extrovert	0.74	42.90%
4	Q11A = Disagree → class_InEx = Extrovert	0.73	39.04%
5	Q18A = Agree → class_InEx = Extrovert	0.73	39.23%

Tables 3 and 4 present five selected single-dimensional rules, accompanied by their confidence and accuracy values, categorized by personality type, with Table 3 for introverts and Table 4 for extroverts. These features, identified by the association rules, were chosen to test a new association rule model. The focus was on selecting rules with the highest accuracy values, using five features for each personality type. Subsequently, these single-rule associations were combined to create new two-rule associations.

4.2. **Evaluating the performance of the association rule model.** This step involves developing a new association rule model by combining single-dimensional rule features. The experiment applied 2-rule association model to testing whether increasing feature associations affects accuracy. The new rules were compared to initial single-dimensional rules, as multi-feature associations can sometimes lead to decreased accuracy. According to the Apriori algorithm, which identifies frequently co-occurring itemsets, associations between multiple features generally occur less often than individual features.

As shown in Table 5, combining single-dimensional features does not reduce accuracy when generating new association rules.

TABLE 5. Comparing the accuracy of a single-dimensional rule and a two-rule association

No.	Association rule	Confidence	Accuracy
	Introvert: Single-dimensional rule		
	Q81A = Agree → introvert	0.95	96.52%
	Introvert: 2-rule association for introvert class		
1	Q81A = Agree, Q80A = Disagree → introvert	0.45	98.49%
2	Q81A = Agree, Q14A = Disagree → introvert	0.42	98.36%
3	Q81A = Agree, Q10A = Agree → introvert	0.41	98.04%
	Extrovert: Single-dimensional rule		
	Q82A = Disagree → Extrovert	0.89	68.81%
	Extrovert: 2-rule association for introvert class		
1	Q82A = Disagree, Q18A = Agree → extrovert	0.58	80.48%
2	Q82A = Disagree, Q51A = Disagree → extrovert	0.42	79.77%
3	Q82A = Disagree, Q85A = Disagree → extrovert	0.70	74.32%

Table 5 compares the accuracy of single-dimensional association rules with 2-rule associations. The accuracy of the newly created association rules is generally higher, although the confidence value may be lower due to the infrequent occurrence of feature pairs. For example, the rule combining Q81A = Agree ("*I am quiet around strangers*") and Q80A = Disagree ("*I love large parties*") identifies the introvert class with a confidence value of 0.45.

When these association rules are combined, the prediction accuracy for the introvert class reaches 98.49%, which is higher than the accuracy of the single-dimensional rule Q81A = Agree → introvert at 96.52%, the highest accuracy achieved by a single feature.

A single-dimensional rule, derived from only one feature, is strongly characterized by that feature, effectively classifying individuals as introvert or extrovert. Such rules are typically limited in number but often offer high accuracy.

In testing association rules by combining one feature from a single-dimensional rule with a distinct feature from another single-dimensional rule, the resulting rule achieves significantly higher accuracy than those generated solely through the Apriori algorithm. However, the confidence value for these newly combined rules may be lower because the combined features occur together less often and have weaker associations. The accuracy remains high, as shown by the 2-rule association method in Table 5.

5. **Conclusion.** Individuals with introverted and extroverted personality types display distinct behavioral patterns that affect work performance. This research aims to improve the accuracy of feature combinations by developing association rules through the Apriori algorithm. By identifying relevant factors linked to each personality type, the model achieves higher accuracy than existing methods. Once an effective model is established, it can be used to analyze and develop strategies for fostering collaboration in team environments.

In this study, a machine learning process was applied to analyzing data for model construction, specifically using the Apriori algorithm with a support value of 0.3 and a confidence value of 0.25. Association rules were categorized into two classes: introvert and extrovert. This research focuses on single-dimensional association rules, each involving only one feature, which are then combined with other single-dimensional features to create new rules. The performance of these new rules is evaluated based on accuracy values, demonstrating an effective approach to personality analysis.

Future research could explore alternative techniques for handling imbalanced data, such as ADASYN, Borderline SMOTE, and IR-SMOTE [24-26] to compare their effectiveness in enhancing personality classification. Additionally, applying deep learning and transformer models is recommended to improve classification accuracy and robustness [27].

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REFERENCES

[1] A. Graf-Nold, Jung, Carl Gustav (1875-1961), *International Encyclopedia of the Social & Behavioral Sciences*, pp.902-906, 2015.

[2] P. Sánchez-Fernández, L. G. B. Ruiz and M. D. C. Pegalajar Jiménez, Application of classical and advanced machine learning models to predict personality on social media, *Expert. Syst. Appl.*, vol.216, 119498, 2023.

[3] B. Zarouali, T. Dobber and J. Schreuder, Personality and susceptibility to political microtargeting: A comparison between a machine-learning and self-report approach, *Comput. Human Behav.*, vol.151, 108024, 2024.

[4] S. Gonzalez-Torre, A. Rasero, A. Diaz-Artiles, M. A. Ramallo and G. G. de la Torre, Latent personality profiles of analog astronauts: An unsupervised clustering method analysis, *Acta Astronaut*, vol.225, pp.898-906, DOI: 10.1016/j.actaastro.2024.10.007, 2024.

[5] R. Yan et al., Exploratory machine learning modeling of adaptive and maladaptive personality traits from passively sensed behavior, *Future Generation Computer Systems*, vol.132, pp.266-281, 2022.

[6] G. Moradi, L. Omidi, S. Vosoughi, H. Ebrahimi, A. Alizadeh and I. Alimohammadi, Effects of noise on selective attention: The role of introversion and extraversion, *Applied Acoustics*, vol.146, pp.213-217, DOI: 10.1016/j.apacoust.2018.11.029, 2019.

[7] O. S. Itani, R. E. Haddad and A. Kalra, Exploring the role of extrovert-introvert customers' personality prototype as a driver of customer engagement: Does relationship duration matter?, *Journal of Retailing and Consumer Services*, vol.53, 101980, 2020.

[8] S. Zulfiqar, M. R. Khawar, B. Sarwar and C. Huo, The role of personality type in overcoming workplace distractions, *Journal of Innovation & Knowledge*, vol.8, no.3, 100381, 2023.

[9] S. D. Vishnubhotla and E. Mendes, Exploring the relation between personality traits and agile team climate: Aggregating results from a twice replicated study in a telecom company, *J. Syst. Softw.*, vol.210, 111937, 2024.

[10] S. Kucukozer-Cavdar and T. Taskaya-Temizel, Analyzing the effects of the personality traits on the success of online collaborative groups, *Procedia Soc. Behav. Sci.*, vol.228, pp.383-389, 2016.

[11] A. Nouwen, S. S. Deschênes, Z. Balkhiyarova, J. R. Albertorio-Díaz, I. Prokopenko and N. Schmitz, Measurement invariance testing of the patient health questionnaire-9 (PHQ-9) across people with and without diabetes mellitus from the NHANES, *J. Affect. Disord.*, vol.292, pp.311-318, 2021.

[12] H. Delamain et al., Measurement invariance and differential item functioning of the PHQ-9 and GAD-7 between working age and older adults seeking treatment for common mental disorders, *J. Affect. Disord.*, vol.347, pp.15-22, 2024.

[13] S. Huda and A. Chowanda, Personality prediction from text on social media with machine learning, *ICIC Express Letters*, vol.15, no.12, pp.1243-1251, 2021.

[14] Y. Bai, Y. Hu, Z. Zhou, X. Du, Y. Shi and L. You, Rise above prejudice against personality: Association with personality and interactive collaboration in team creativity performance, *Think. Skills Creat.*, vol.52, 101539, 2024.

[15] D. L. Robinson, Conceptual and methodological errors that invalidate Luciano et al.'s claim to have tested Robinson's theory of personality and intelligence, *Pers. Individ. Dif.*, vol.44, no.1, pp.273-277, 2008.

[16] R. Agrawal and R. Srikant, Fast algorithms for mining association rules in large databases, *Proc. of the 20th International Conference on Very Large Data Bases*, pp.487-499, 1994.

[17] X. Geng, Q. Sun, Z.-J. Zhou, L. Jiao and Z. Ma, Adaptive fuzzy-evidential classification based on association rule mining, *Inf. Sci. (NY)*, vol.665, 120408, 2024.

[18] X. Wang, C. Song, W. Xiong and X. Lv, Evaluation of flotation working condition recognition based on an improved apriori algorithm, *IFAC-PapersOnLine*, vol.51, no.21, pp.129-134, 2018.

[19] K. Nasritha, K. Kerdprasop and N. Kerdprasop, Comparison of sampling techniques for imbalanced data classification, *Journal of Applied Informatics and Technology*, vol.1, no.1, pp.20-37, 2018.

[20] G. Ryan, P. Katarina and D. Suhartono, MBTI personality prediction using machine learning and SMOTE for balancing data based on statement sentences, *Information*, vol.14, no.4, 217, 2023.

[21] T. Fahrudin, J. L. Buliali and C. Fatichah, Enhancing the performance of SMOTE algorithm by using attribute weighting scheme and new selective sampling method for imbalanced data set, *International Journal of Innovative Computing, Information and Control*, vol.15, no.2, pp.423-444, 2019.

[22] Q. Xiao, F. Luo, Y. Li and D. Pan, Risk prediction and early warning of pilots' unsafe behaviors using association rule mining and system dynamics, *J. Air. Transp. Manag.*, vol.110, 102422, 2023.

[23] F. Peng, Y. Sun, Z. Chen and J. Gao, Association rule mining of maritime employ ability demands based on Apriori algorithm, *ICIC Express Letters, Part B: Applications*, vol.14, no.6, pp.633-639, 2023.

[24] T. A. Assegie, A. O. Salau, K. Sampath, R. Govindarajan, S. Murugan and B. Lakshmi, Evaluation of adaptive synthetic resampling technique for imbalanced breast cancer identification, *Procedia Comput. Sci.*, vol.235, pp.1000-1007, 2024.

[25] J. Guo, H. Wu, X. Chen and W. Lin, Adaptive SV-Borderline SMOTE-SVM algorithm for imbalanced data classification, *Appl. Soft. Comput.*, vol.150, 110986, 2024.

[26] H. Guan, L. Zhao, X. Dong and C. Chen, Extended natural neighborhood for SMOTE and its variants in imbalanced classification, *Eng. Appl. Artif. Intell.*, vol.124, 106570, DOI: 10.1016/j.eng appai.2023.106570, 2023.

[27] X. Wu et al., CTransCNN: Combining transformer and CNN in multilabel medical image classification, *Knowl. Based Syst.*, vol.281, 111030, 2023.