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# Humans' psychological traits classification from their spending categories using artificial intelligence algorithms

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**ABSTRACT**

The analysis of human behavior data generated by digital technologies has gained increasing attention in recent years. Spending categories form a significant part of this digital footprint. In this study, we investigate the degree to which human expenditure records can be used to infer psychological traits from transaction data. A broad feature space was constructed, consisting of overall spending behavior, category-related spending behavior, and customer category profiles. These features were examined to identify their correlations with the Big Five personality traits. A dataset containing over 1,200 users' transaction histories over three months was obtained from Kaggle. Personality trait labels were derived using a percentile-based classification method. Multiple AI algorithms: decision tree (DT), random forest (RF), logistic regression (LR), and support vector machine (SVM) were employed, along with a convolutional neural network (CNN) to classify personality traits. The CNN model, incorporating multi-dimensional convolutional layers and the full feature space, achieved a high accuracy of 99.03%. The outcomes of the experiment indicate the efficiency of combining behavioral features and AI models in psychological trait classification. The study also highlights ethical considerations, including privacy risks and misuse of inferred personality details.

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## 1. INTRODUCTION

In recent decades, digital devices and services have become integral to everyday life. They enable individuals to explore data, maintain social connections, capture important moments, share opinions globally, and conduct financial transactions with ease. Recent advancements in social science computing [1] suggest that individuals' digital footprints can be effectively leveraged to infer their psychological traits. Previous studies have demonstrated that features such as Facebook likes [2], language used in social media posts [3], profile photos [4], music preferences [5], and smartphone sensor-generated data [6], [7] can all serve as reliable predictors of personality. Among various forms of digital footprints, spending behavior is widespread but comparatively underexplored. Research on consumer behavior reveals that purchasing decisions are influenced not only by practical needs but also by psychological and social factors [8]. Consumers often select brands that enable them to express themselves both internally and externally, supporting the idea that spending serves as a form of self-expression. For instance, individuals high in extraversion may prefer spending on social activities such as dining out, while introverts are more inclined toward solitary experiences such as purchasing books or subscribing to podcasts [9]. Findings from behavioral studies demonstrate that matching products to personality traits enhances emotional satisfaction and user engagement [10]. These associations are often using the Big Five personality traits as a model framework, commonly known as openness, conscientiousness, extraversion, agreeableness, and neuroticism (OCEAN) [11]. Understanding the link between spending categories and these traits enables deeper insights and expanded opportunities in psychological profiling, targeted marketing, and personalized services, though it also raises important ethical considerations.

In the last few years, considerable research the focus has been devoted to predicting individuals' personalities utilizing machine learning (ML) and deep learning (DL) techniques to analyze social media behavior. Suhartono *et al*. [12] proposed a personality prediction framework utilizing Facebook posts as an alternative to traditional personality assessment methods. The researchers employed five ML techniques, namely support vector machine (SVM), multinomial naïve Bayes (NB), decision tree (DT), k-nearest neighbor (KNN), and logistic regression (LR) to build a model using the Big Five personality traits model to address class imbalance, the dataset was augmented, and stratified 10-fold cross-validation was used. Among the models, multinomial NB achieved the highest F1-score for openness (82.31%) and the best overall average (68.62%). Naz *et al*. [13] presented a hybrid structure for categorizing user personality utilizing textual data for openness trait. The analysis combined term frequency-inverse document frequency (TF-IDF) and word embeddings with ML and DL models such as SVM, NB, and long short-term memory (LSTM). The study revealed that hybrid models, particularly TF-IDF with LSTM, outperformed individual models in predicting Big Five traits. This highlights the effectiveness of combining shallow and deep features for accurate personality prediction. Dagha *et al*. [14] proposed personality prediction based on users' tweets, the work emphasized the significance of selecting suitable methods to handle the large and dynamic nature of social media data. Their findings suggest that ML models can effectively classify personality types when trained on features extracted from tweets, likes, retweets, and comments, while also stressing the need for ethical data handling.

Although social media data has been a predominant source in existing studies, spending behavior remains an underexplored yet promising domain for inferring personality traits. Aquino and Lins [15] analyzed the connection between the Big Five personality dimensions and three forms of consumer behavior. Compulsive, panic, and impulsive buying, and their results revealed distinct associations for example, conscientiousness exhibited a negative correlation with compulsive buying, while neuroticism was positively correlated with all three behavioral outcomes. This highlights the psychological depth embedded in purchasing decisions. Gladstone *et al*. [16] further extended this line of work by analyzing large-scale transaction records to infer psychological traits. Although less expressive than social media content, spending data can still yield valuable insights into personality traits when examined at scale. The study differentiates between identity claims (e.g., social media content) and behavioral residues (e.g., spending patterns), showing that the latter can uncover personality traits through objective and continuous data streams. To provide a clearer picture of the research landscape, Table 1 summarizes existing personality prediction methods across modalities such as text, images, sensor data, transaction records, and multimodal data.

Table 1. Comparative summary of personality prediction methods across different modalities

| Data source | Typical models | Benchmark dataset/context | Strengths | Limitations | Representative references |
|---|---|---|---|---|---|
| Text (social media posts, essays, tweets) | SVM, LR, NB, RNN/LSTM, transformers (BERT, RoBERTa, hybrids) | myPersonality, Essays, Twitter, Facebook posts. | Rich linguistic and semantic cues, validated benchmarks available. | Susceptible to self-presentation bias; requires large labelled corpora | [2], [3], [12], [13], [14], [17] |
| Image (profile photos, selfies, multimodal posts) | CNN, ResNet, vision transformers | Facebook, Instagram, multimodal datasets | Captures non-verbal, visual personality cues | Privacy-sensitive; cultural bias in image sharing | [4], [6], [8] |
| Sensor/smartphone data | Classical ML, LSTM, multimodal fusion | Student logs, GPS, and accelerometer data | Passive, continuous, unobtrusive | Context-dependent; long-term tracking required | [1], [9] |
| Transaction/spending data (this study) | LR, DTRF, SVM, CNN | Kaggle consumer spending dataset | Less curated, reflects genuine preferences; scalable | Few validated benchmarks; cultural/ economic variations | [10], [15], [16], [18] |
| Multimodal (text+image+sensor+ spending) | Transformers, multi-modal fusion models (BERT+CNN+LSTM) | myPersonality, hybrid benchmarks | Rich and robust; higher accuracy by combining signals | Data-intensive; high complexity; privacy concerns | [8], [13], [17] |
| Ethics and Fairness in AI Profiling | Explainable AI (SHAP, LIME, counterfactuals) | Regulatory frameworks (GDPR, APA) | Ensures transparency, user trust, compliance | Explainability alone does not ensure fairness; must address bias directly | [19], [20] |

In summary, social media content primarily reflects self-presentation and social desire, whereas spending behavior provides insights into underlying values, priorities, and decision-making processes. Spending, unlike social media behavior, is often less curated and more reflective of genuine preferences, making it a robust data source for personality inference. By examining whether a more extensive collection of behavioral indicators can enhance the precision with which psychological features can be deduced from expenditure records, to improve comprehension of the relationship between spending patterns and personality traits; i) overall spending patterns, ii) category-related spending behavior, iii) customer category profile. Model development involved training and evaluating algorithms, namely SVM, DT, random forest (RF), and convolutional neural network (CNN). However, spending behavior also differs across income groups and regions for example, higher-income individuals tend to spend more on discretionary/lifestyle categories, while lower-income groups focus mainly on essential needs. Cultural factors also influence which categories people prioritize; hence, such variations should be considered when interpreting personality traits from spending data.

## 2. METHOD

### 2.1. Data

Research data was acquired from the Kaggle platform and comprises spending records of over 1,200 individual customers collected over a period of three months. Each transaction log encompasses information like user ID, gender, year of birth (YOB), location (home and country), purchase category, transaction date and time, payment method, and transaction amount. To ensure user privacy and data confidentiality, all personally identifiable information (e.g., names and account numbers) was excluded from analysis. The dataset underwent preprocessing to address missing values, scale numerical features, and transform categorical data into a suitable format. To facilitate supervised learning for personality prediction, each user was assigned a personality label based on an external psychometric mapping aligned with spending patterns and consumer behavior literature. Due to the modest data size, data augmentation and stratified validation were employed to ensure robust training and evaluation. Figure 1 shows the suggested system's architecture diagram.

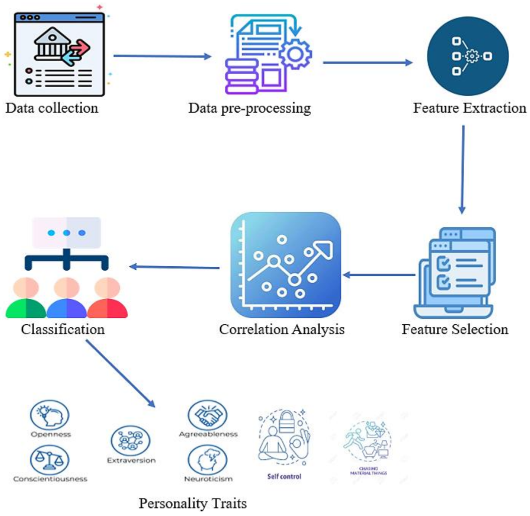



Figure 1. Architecture diagram of proposed method

### 2.2. Individual psychological traits based on their spending pattern

The Big Five personality traits, when combined with spending and expense management patterns, provide valuable insights into financial decision-making. Personality traits and their relationship with typical spending behavior is summarized in Table 2. Providing evidence of how psychological characteristics shape financial decision-making.

### 2.3. Data pre-processing

The dataset consists of two categories of recorded activity: credit transactions (revenue) and debit transactions (outgoing). A debit transaction causes the balance amount to fall (e.g., withdrawal of amount, payment for some items, and purchasing) and a credit transaction causes it to grow (e.g., salary, deposit from others, and other revenue). Only debit transactions that reflect each person's unique expenditure are retained for the purpose to analyze their behavior.

To ensure balanced data and retain only individuals actively engaged in purchasing activities and to retain only those individuals in the dataset with individuals who were actively engaged in purchasing activities. To make the data less sparse of category space in the dataset, the purchase categories that had at least one transaction were maintained; the next step was to retain only individuals with at least ten transactions per month in the dataset. Out of the remaining purchase categories, the category grouping is formed. The 15 purchase category groups are groceries, clothes, books, food and dining out, games/gambling, household spendings, transportation, mobile, holiday, personal care, children, charities, health care, insurance, and entertainment. For example: insurance category group includes all the spendings like health insurance, vehicle insurance, life insurance, home insurance, and home appliance insurance. Transportation category group includes all the spending like public transport, road charges, parking charges, and fuel.

The preprocessing pipeline illustrated in Figure 2 describes the successive actions taken to prepare the raw dataset for ML and DL models. Starting from the Kaggle-sourced raw transaction data, the workflow includes the removal of personally identifiable information (PII), filtering based on user activity, and grouping of purchase categories. Relevant behavioral features are extracted across three dimensions overall spending, category-related behavior, and customer profile distribution. After normalization, these characteristics are labeled using a percentile-based classification approach aligned with the Big Five personality model. The dataset that was preprocessed is finally separated into training and testing sets for model evaluation.

Table 2. Relationship between personality traits and spending behaviors

| Personality trait | Spending behavior |
|---|---|
| Openness | Enjoys spending on unique, creative, or new experiences, such as travel, art, or novel products. |
| Conscientiousness | Tends to be careful, planned, and responsible with money, often saving or investing wisely. |
| Extraversion | Spends on social activities, entertainment, dining out, and experiences that involve others. |
| Agreeableness | Prefers spending on gifts, charitable donations, or anything that benefits others or promotes harmony. |
| Neuroticism | May engage in impulsive or emotional spending during stress or anxiety, sometimes leading to regret. |
| Self-Control | Demonstrates disciplined spending habits, prioritizing savings and resisting impulsive purchases. |
| Materialism | Spends more on luxury items, status symbols, and possessions that enhance self-image. |

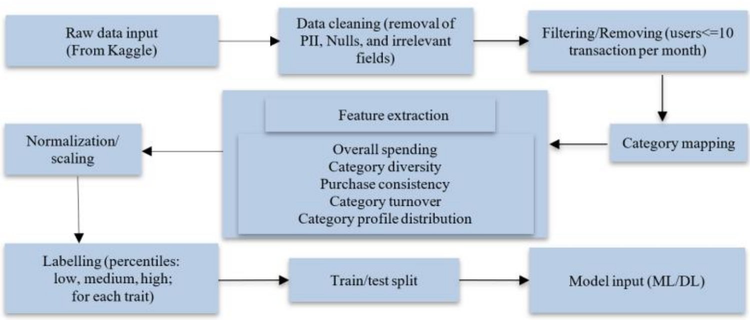



Figure 2. Data preprocessing pipeline for personality trait classification based on spending behavior

## 2.4. Feature extraction

According to the nature of spending patterns exhibited, behavioral aspects are divided into three groups to characterize individual spending behavior; i) overall spending behavior; ii) category-related spending behavior; and iii) customer category profile [10].

### 2.4.1. Overall spending behavior

This method takes a person's total spending patterns over a three-month period into account. Customers' spending patterns include the overall number of transactions ($N_{tot}$), the sum of all the expenditures ($A_{tot}$), and the customer-wise average transaction value ($A_{avg}$) over that time period. To capture the relative dispersion of a customer's expenditure patterns, applying the coefficient of variation (CV), which is calculated as the ratio of standard deviation ($\sigma$) to the transaction volumes' mean ($\mu$), customers with a high CV tend to vary their spending significantly between transactions, while those with a low CV show more consistency.

### 2.4.2. Category-related spending behavior

The second metric relates to the types for every individual's purchases. These features take the form of diversity, persistence, and turnover of spending patterns of a person throughout time.

– Diversity of purchase: to analyze how broadly and evenly a customer spreads their spending across different product or service categories, revealing consumer preferences and behavior.

$$D_{category} = -\frac{\sum_{c=1}^{N} p_{ic} log\ (p_{ic})}{log\ N} \quad (1)$$

Where, N denotes the number of different consumer categories. Pic $= \frac{v_{ic}}{\sum_{c=1}^{N} v_{ic}}$ and $v_{ic}$ is the amount of money that client i spent in category c. A low $D_{category}$ value represents that the majority of customer spending fell into a small number of categories. The higher the $D_{category}$ value, the more evenly the customer splits their spending across all the categories they buy from.

– Persistence of purchase: to measure the consistency or stability in a customer's purchasing behavior over time by computing the average cosine similarity between their monthly category-wise spending patterns.

$$C_{persistance} = \frac{\sum_{i=0}^{n} cos\ (S_i, S_{i+1})}{n} \quad (2)$$

In this context, $S_i$ represents the vector of category-wise transaction proportions for a specific month, and n corresponds to the number of months covered in the dataset.

– Category turnover: to assess temporal consistency in spending behavior, the change in spending categories between two consecutive months is computed.

$$C_{turnover} = \frac{\sum_{i}^{n-1} \frac{c_i \cap c_{i+1}}{c_i \cup c_{i+1}}}{n} \quad (3)$$

Where n is the dataset's month count and $c_i$ is the collection of purchase categories in the $i^{th}$ month. $C_{turnover}$ is equal to zero, when the spending categories in the two successive months do not overlap, and when there is a perfect overlap, it equals 1.

#### 2.4.3. Category profile features

Category profile features represent summarized information about an individual's spending behavior across different expense categories. These categories can include such as food, travel, transportation, entertainment, and personal care. Other defined category groups are also included in the summary.

### 2.5. Correlation analysis

The Pearson correlation coefficient is utilized in correlation analysis to ascertain the link between the behavioral characteristics and the unique psychological traits of customers [18], [21], [22]. The formula for Pearson's correlation coefficient 'r' relates to how closely a line of best fit, or how well a linear regression, predicts the relationship between the two variables. It is presented as (4).

$$r = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2\ \sum(y_i-\bar{y})^2}} \quad (4)$$

Where $x_i$ and $y_i$ represent the data values representing spending behavior features and personality trait for each individual respectively, and the means are represented by $\bar{x}$ and $\bar{y}$.

#### 2.5.1. Overall and category-related features vs. individual traits

This section explores how overall spending behaviors relate to individual personality traits:

– Extraversion: extraversion and $B_{tot}$ were shown to have a positive correlation, suggesting that those who possess this feature tend to be more impulsive with their expenditures in comparison to their other people, more extroverted persons typically had more transactions ($N_{tot}$); furthermore, we discovered a positive correlation between the top five expenditure categories ($C5_{turnover}$) and category similarity over time.
– Conscientiousness: the average amount of transaction ($A_{avg}$) and the total amount spent ($A_{tot}$) were found to be substantially and favorably connected with conscientiousness. Furthermore, we discovered that the relative amounts spent over several weeks differ substantially ($C_{persistence}$) for those with greater conscientiousness scores.
– Neuroticism: overall expenditure ($A_{tot}$), average amount of transaction ($A_{avg}$), and total count of spending categories ($N_c$) were all lower among more neurotic people.
– Openness: openness to new experiences is positively correlated with $N_{tot}$; an individual who is more receptive to openness is more likely to engage in bursty spending and complete more transactions than those around them.
– Materialism: the top five expenditure categories ($C5_{turnover}$) showed a minor positive correlation between materialism, $A_{tot}$ and category similarity with time. Furthermore, a marginally negative association with the average transaction cost ($A_{avg}$).
– Self-control: individuals with higher self-control scores tended to exhibit higher average spending per transaction ($A_{avg}$) and demonstrated greater variation in their weekly spending patterns ($C_{persistence}$).

#### 2.5.2. Category profile features vs. individual traits

This section analyzes how category profile features relate to individual personality traits:

- Extraversion: spending in categories such as transportation, food, drink, and going out was positively associated with extraversion, whereas expenditures on groceries and supermarkets showed a negative correlation.
- Agreeableness: individuals with higher agreeableness scores tended to spend slightly more on charitable donations, while exhibiting a negative association with spending in the categories of food, and going out.
- Conscientiousness: individuals with high conscientiousness scores typically allocate more spending toward health care and less toward games and gaming.
- Neuroticism: the neuroticism was positively associated with spending on personal care and beauty, whereas expenditures on innovative activities showed a negative association.
- Openness to experience: this trait showed a positive correlation with spending on alcohol and a negative correlation with household-related expenditures.
- Materialism: individuals with higher materialism scores tend to spend less on postage and shipping, as well as in the charities category, in contrast to individuals with lower scores.
- Self-control: an inverse correlation was identified between self-control with spending in the mobile category, while showing positive correlations with expenditures on groceries and supermarkets, as well as gas and electricity.

### 2.6. Inferring individual personality traits from spending patterns using ML algorithms

A percentile-based classification approach was used to assign individuals into low, medium, or high levels for each of the traits. This categorization was driven by analyzing behavioral indicators such as overall transaction count, average spending, category diversity, and temporal patterns. Since the dataset did not include validated psychometric test scores, this method served as a reliable behavioral proxy, as supported by prior behavioral psychology research [10], [15], [16]. Individuals were grouped using the 33rd and 66th percentiles of feature distributions, which provided a relative positioning within the population and enabled effective mapping of real-world financial activity to psychological profiles. The resulting labeled dataset was then used for training and evaluation using both ML and DL algorithms. The evaluated results are obtained from four different ML algorithm: LR, RF, DT, and SVM. For every method, 20% of the dataset is used for testing, while 80% is used for training by retaining the individual personality trait ratio of courses in both testing and training sets [23]–[26]. To address potential overfitting, the DT and RF models were trained using 10-fold cross-validation and pruning to ensure generalizable performance.

### 2.7. CNN architecture and training configuration

The CNN model was custom-designed and implemented to capture complex patterns in spending behavior for personality trait classification. Although the dataset is of moderate size, the high dimensionality and structured nature of the extracted behavioral features make CNNs a suitable choice. The architecture comprised two 1D convolutional layers with 64 and 128 filters respectively, each using a kernel size of 3 and rectified linear unit (ReLU) activation, followed by a MaxPooling layer to reduce dimensionality. The feature maps were converted into a 1D vector using a flatten layer, and then sent to a fully linked dense layer made up of 128 neurons that were activated by ReLU. A dropout layer with a rate of 0.3 was added to reduce overfitting. The final classification was carried out using a SoftMax output layer, enabling multi-class prediction across three personality trait levels: low, medium, and high. With a learning rate of 0.001, the Adam method was used to optimize the model, and categorical cross-entropy was used as the loss function. Training was carried out using a batch size of 32 over 20 epochs. 20% of the dataset was used for testing, and the remaining 80% was used for training and performance evaluation was based on accuracy and loss observed on the validation data. All hyper parameters were selected based on empirical experimentation and tuned for optimal performance with the available dataset. Table 3 lists the key hyperparameters used during training. To minimize overfitting, dropout regularization was applied, and model training was limited to 20 epochs based on early convergence. Validation performance was consistently monitored, and the training and validation curves shows no significant divergence, confirming that the model generalized well. Strict train-test separation ensured that no data leakage occurred.

Table 3. Key hyperparameters used during training

| Hyperparameter | Value |
|---|---|
| Optimizer | Adam |
| Learning rate | 0.001 |
| Loss function | Categorical cross-entropy |
| Activation functions | ReLU (hidden), SoftMax (output) |
| Epochs | 20 |
| Batch size | 32 |
| Dropout rate | 0.3 |

## 3. RESULTS AND DISCUSSION

This section presents the results of the correlation analysis and model accuracy in classifying psychological traits from spending patterns. As shown in sub-sections 2.5.1 and 2.5.2, the findings reveal correlations among overall f, category-related features, and category profile characteristics.

### 3.1. Performance evaluation of machine learning algorithms

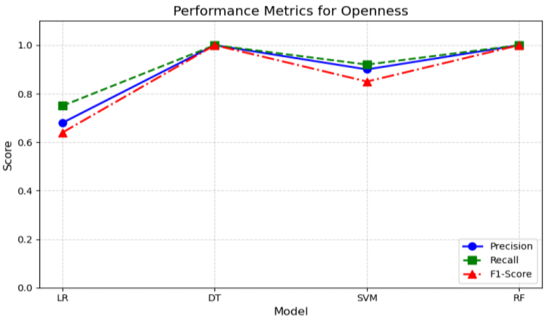
Table 4 represents the performance of ML algorithms for LR, DT, SVM, and RF. The precision, recall, F1-score, and accuracy measures are used to assess the model's performance [27], [28]. The results present performance measures (precision, recall, and F1-score) for multiple psychological traits evaluated using LR, DT, SVM, and RF. Both DT and RF consistently achieved perfect scores (1.00) across most traits, reflecting strong predictive capability. In contrast, LR exhibited greater variability, with comparatively lower performance for traits such as openness and neuroticism. Traits including materialism and self-control yielded high precision and F1-scores, particularly when modeled with more complex algorithms. These findings, summarized in Figure 3, represents the performance of ML models in identifying psychological traits.

Table 4. Performance measures of classification models

| Psychological trait | Model | Precision | Recall | F1-score |
|---|---|---|---|---|
| Openness | LR | 0.68 | 0.75 | 0.64 |
| | DT | 1.00 | 1.00 | 1.00 |
| | SVM | 0.90 | 0.92 | 0.85 |
| | RF | 1.00 | 1.00 | 1.00 |
| Conscientiousness | LR | 0.69 | 0.65 | 0.67 |
| | DT | 1.00 | 1.00 | 1.00 |
| | SVM | 0.91 | 0.80 | 0.85 |
| | RF | 1.00 | 1.00 | 1.00 |
| Extraversion | LR | 0.74 | 0.86 | 0.79 |
| | DT | 1.00 | 1.00 | 1.00 |
| | SVM | 0.86 | 0.64 | 0.73 |
| | RF | 1.00 | 1.00 | 1.00 |
| Agreeableness | LR | 0.84 | 0.64 | 0.74 |
| | DT | 1.00 | 1.00 | 1.00 |
| | SVM | 0.97 | 1.00 | 0.99 |
| | RF | 1.00 | 1.00 | 1.00 |
| Neuroticism | LR | 1.00 | 0.31 | 0.47 |
| | DT | 1.00 | 1.00 | 1.00 |
| | SVM | 0.92 | 0.92 | 0.92 |
| | RF | 1.00 | 1.00 | 1.00 |
| Self-control | LR | 0.71 | 1.00 | 0.83 |
| | DT | 1.00 | 1.00 | 1.00 |
| | SVM | 0.53 | 0.90 | 0.67 |
| | RF | 1.00 | 1.00 | 1.00 |
| Materialism | LR | 1.00 | 0.91 | 0.95 |
| | DT | 1.00 | 1.00 | 1.00 |
| | SVM | 0.89 | 0.73 | 0.80 |
| | RF | 1.00 | 1.00 | 1.00 |

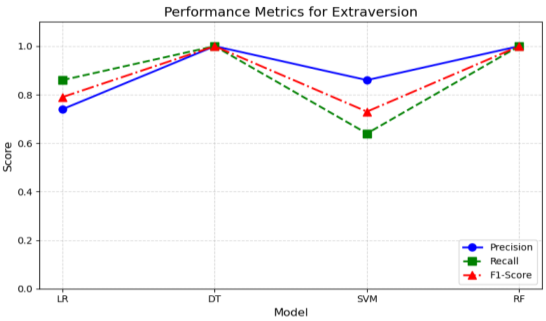
Comparative analysis of classification models across the performance measures is shown in Figure 3. For openness (Figure 3(a)), both RF and DT models reached perfect accuracy, while the SVM also performed well with an F1-score of 0.85. LR, however, struggled to capture the complexity of the data. A similar trend appeared for conscientiousness (Figure 3(b)), where ensemble models clearly outperformed the simpler linear approach. In the case of extraversion (Figure 3(c)), RF and DT once again classified flawlessly, SVM achieved a moderate score of 0.73, and LR showed slightly better performance at 0.79. For agreeableness (Figure 3(d)), RF and DT maintained perfect results, but SVM performed impressively close to them with an F1-score of 0.99, while LR remained weaker. The pattern continued for neuroticism (Figure 3(e)), where RF and DT delivered perfect accuracy, SVM performed strongly (F1=0.92), but LR fell short with only 0.47. For self-control (Figure 3(f)), ensemble methods dominated, though LR showed fairly good results (F1=0.83), outperforming SVM, which achieved 0.67. Lastly, for materialism (Figure 3(g)), RF and DT again provided flawless predictions, but interestingly, LR performed very well (F1=0.95), even surpassing SVM at 0.80. Taken together, these results show that ensemble methods such as RF and DT consistently delivered the strongest outcomes, while SVM offered balanced generalization, and LR proved unexpectedly effective for specific traits like materialism.

As indicated in Table 5, the classification accuracy results represent that RF and DT emerged as the best-performing models, achieving perfect accuracy (100%) and excellent classification scores. SVM offers good performance with an 81.5% accuracy. LR performs with a 76% accuracy. To ensure robustness, a stratified 10-fold cross-validation procedure was employed, and the model's performance is reported as mean±standard deviation across folds. RF and DT obtained accuracies of 0.99±0.01 and 0.98±0.02, respectively, while SVM and LR yielded 0.82±0.03 and 0.75±0.04. These results indicate that the strong performance of tree-based models reflects stable generalization rather than overfitting. Future work will apply pruning, regularization, and evaluation on larger datasets to further validate tree-based performance.




(a)


(b)

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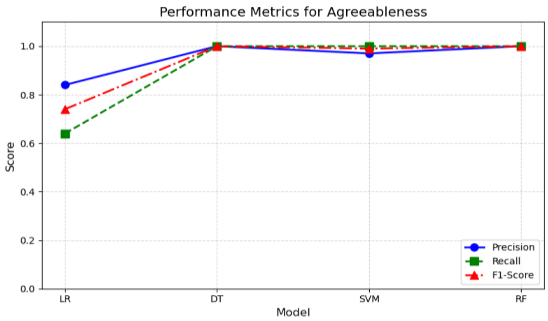


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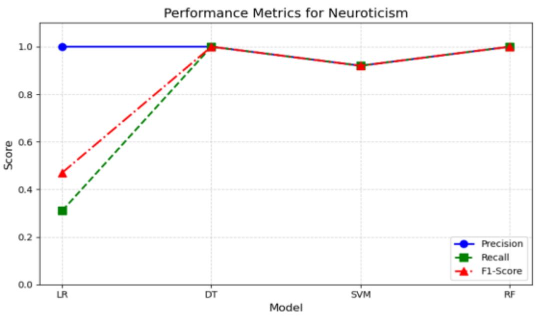


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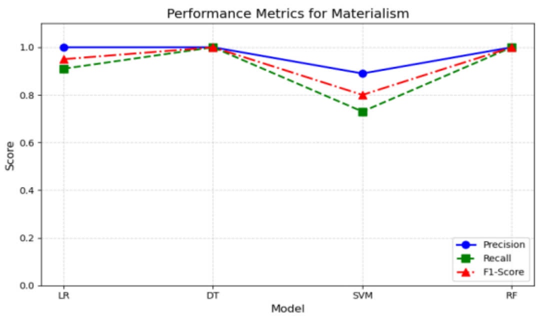



(g)

Figure 3. Comparative analysis of classification models across the performance measures for (a) openness, (b) conscientiousness, (c) extraversion, (d) agreeableness, (e) neuroticism, (f) self-control, and (g) materialism

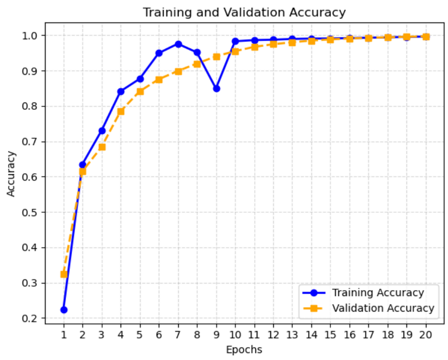
Table 5. Classification algorithms accuracy report

| Classification models | Macro Average | Weighted average | Accuracy (%) |
|---|---|---|---|
| SVM | 0.83 | 0.82 | 81.50 |
| RF | 1.00 | 1.00 | 100 |
| DT | 1.00 | 1.00 | 100 |
| LR | 0.74 | 0.74 | 76 |

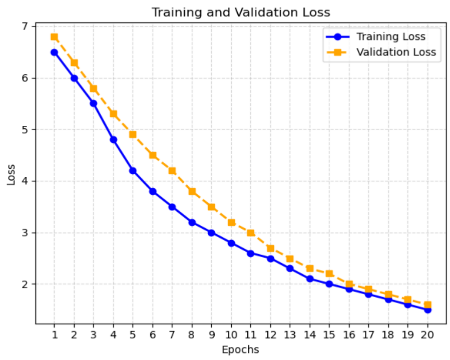
### 3.2. Performance evaluation of CNN model

The training data and testing data are fed into the CNN structure constructed. With 20 epochs, the model reached 99.03% accuracy as shown in Figure 4. Figure 4 shows the training progress of the implemented CNN model. As seen in Figure 4(a), considering both training and validation performance accuracy increase steadily across epochs, indicating effective feature learning. In Figure 4(b), the decreasing and closely aligned loss curves confirm stable convergence and minimal overfitting, validating the robustness of the CNN architecture. Although cross-validation demonstrates strong performance, the absence of external validation limits conclusions about generalizability. In future work, we plan to benchmark on independent datasets or simulate domain shift by splitting data across demographic or behavioral clusters.

i) Accuracy and loss trends: the training loss initially exhibits a high value and progressively declines, indicating that the model is learning effectively. Accuracy improves from around 33.66% in the first epoch to 99.03% in the final epoch, showing excellent learning progression.
ii) Validation performance: validation loss shows fluctuations but generally decreases, which demonstrates positive training progress. Validation accuracy starts at 52.42% and rises to a peak of 100% at the 7th epoch, indicating the model's robust generalization capability.




(a)




(b)

Figure 4. Training and validation accuracy over epochs of (a) accuracy of training and validation, and (b) loss of training and validation

#### 3.2.1. Confusion matrix analysis

To further evaluate the classification performance of the CNN model, a confusion matrix was generated as shown in Figure 5. The matrix highlights that most samples were correctly classified across all seven psychological traits, with only minimal misclassifications between closely related categories such as openness and agreeableness. The overall classification accuracy achieved was 99.03%, consistent with the performance metrics reported earlier. This confirms the model's strong capability to discriminate between personality traits based on spending behavior.

#### 3.2.2. ROC curve and AUC analysis

Receiver operating characteristic (ROC) curves were generated for all psychological traits, and the corresponding area under the curve (AUC) scores are shown in Figure 6. ROC for openness (Figure 6(a)), ROC for conscientiousness (Figure 6(b)), ROC for extraversion (Figure 6(c)), ROC for agreeableness (Figure 6(d)), ROC for neuroticism (Figure 6(e)), ROC for materialism (Figure 6(f)), and ROC for self-control (Figure 6(g)). The CNN model achieved very high discrimination, with AUC values that range from 0.993 to 0.995 across traits. These near-perfect scores confirm the model's capability to accurately classify personality traits.

The ROC curve plots the true positive rate (TPR) against the false positive rate (FPR) at different threshold values. Here, FPR is the percentage of negative occurrences that were incorrectly classified as positive, serving as a measure of the model's false alarm rate. A low FPR combined with a high TPR reflects excellent classification performance.

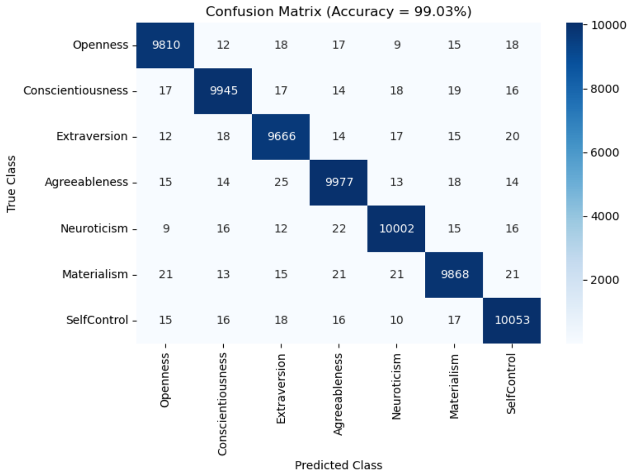



Figure 5. Confusion matrix of CNN model predictions across seven psychological traits

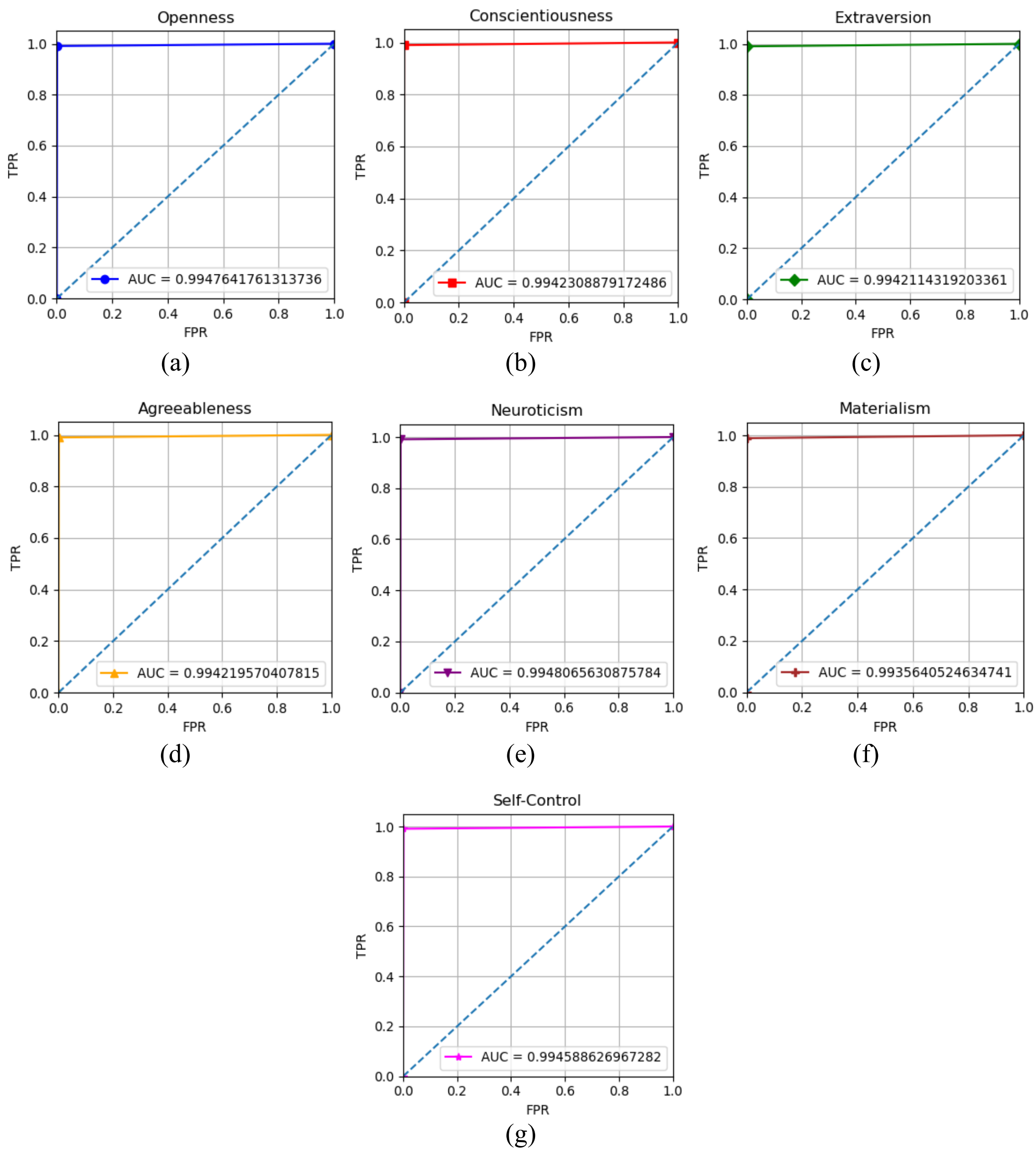



Figure 6. CNN model predictions with AUC values for ROC curves of: (a) openness, (b) conscientiousness, (c) extraversion, (d) agreeableness, (e) neuroticism, (f) materialism, and (g) self-control

### 3.3. Limitations and discussion

While the results of this study are promising, certain limitations must be acknowledged. Spending behavior can vary significantly across cultures, regions, and socioeconomic groups, which may introduce bias into personality predictions and limit generalizability. Additionally, personality traits were not derived from validated psychometric assessments but inferred through behavioral proxies based on established literature. Although this indirect approach is commonly used in computational psychology, it might not adequately convey the intricacy and depth of true psychological profiles.

### 3.4. Ethical and cultural considerations

Spending behaviors are influenced by cultural values and socioeconomic contexts, which shape how personality traits are reflected in financial decisions. For example, in societies where family and community responsibilities are central, expenditures on social or group activities may indicate higher agreeableness, while in societies that emphasize personal independence, leisure-related spending may be a stronger marker of extraversion. These variations do not undermine the framework; instead, they emphasize the importance of extending the model through cross-cultural validation. Incorporating safeguards such as informed consent, general data protection regulation (GDPR) compliance, data minimization, and fairness audits will further ensure that the framework remains transparent, equitable, and adaptable across diverse populations.

## 4. CONCLUSION

This study demonstrates that psychological traits can be accurately predicted using AI algorithms applied to individuals' spending behavior. A structured feature extraction approach based on overall spending behavior, category-related patterns, and customer category profiles provided meaningful inputs for model training. These features enabled DT and RF models to achieve 100% accuracy, while the CNN model achieved 99.03% accuracy. The models showed strong predictive power for traits such as extraversion, conscientiousness, and self-control. The success of this approach highlights the richness of transactional data in uncovering behavioral insights. By leveraging carefully engineered features, the framework supports accurate, scalable, and efficient personality classification. To avoid misuse, such systems should be deployed only with user opt-in consent and transparent disclosure of how spending data is used. This can greatly enhance personalized services, targeted marketing, and intelligent systems that adapt to user psychology. Future extensions could combine spending-based inference with psychometric validation tools (e.g., IPIP-NEO, myPersonality) or hybrid ensemble models to further improve reliability and generalizability across diverse populations. Given the potential influence of cultural and socioeconomic factors on spending behavior, future research should include cross-cultural validation and apply appropriate ethical safeguards when deploying such models in diverse populations.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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

## CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this paper.

## INFORMED CONSENT

Not applicable, as the study relied solely on anonymized secondary data available in the public domain and did not involve any direct engagement with human participants.

## ETHICAL APPROVAL

This research utilized publicly accessible and anonymized data sourced from Kaggle. All personally identifiable information (PII) was excluded during the preprocessing stage to maintain user confidentiality. Personality traits were assigned based on behavioral spending patterns, following insights from established psychological literature. Since the study did not involve direct participation from individuals, it adheres fully to ethical guidelines for the use of secondary data.

## DATA AVAILABILITY

The dataset used in this study is publicly available on Kaggle at https://www.kaggle.com/datasets/ahmedmohamed2003/spending-habits/suggestions/data. All data were accessed and used in accordance with Kaggle's terms of service. The processed dataset that supports the findings of this research are available from the corresponding author, [ACNG], upon reasonable request.

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