UDC 659
DOI: 10.15587/1729-4061.2024.310375

SYSTEM DEVELOPMENT FOR ENHANCING SOCIAL MEDIA ADVERTISEMENT ENGAGEMENT THROUGH XLNET-BASED PERSONALITY CLASSIFICATION

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This research focuses on addressing the challenge of implementing personalized advertisements in the retail industry, where existing methods often face complexities that hinder their swift and large-scale adoption. The primary objective of this study was to develop a scalable and efficient social media advertisement personalization system by employing advanced personality classification techniques. The system utilizes the myPersonality dataset, grounded in the Big 5 OCEAN traits theory, to accurately classify user personalities. By integrating the XLNet model, optimized for personality classification, the system achieves a classification accuracy of 97.47 %, with precision, recall, and F1-Score values of 0.95, 0.94, and 0.94, respectively.

The findings demonstrate that personalized advertisements, driven by accurately classified personality traits, significantly enhance user interaction rates, showing a 24 % improvement over generalized advertisements. This improvement in engagement suggests that the system can effectively personalize advertisements to resonate more deeply with users, fostering stronger connections between users and the advertised content.

The proposed system's high accuracy and improved interaction rates make it a valuable addition to current marketing strategies, enhancing both engagement and conversion rates. This innovative approach has the potential to transform personalized advertising, making it more effective and widely adoptable within the marketing sector

Keywords: personality classification, personalized advertisement, OCEAN traits, big five personality, autoregressive transformer, XLNet, user engagement

Received date 29.05.2024
Accepted date 07.08.2024
Published date 30.08.2024

***How to Cite**: Sandra, L., Prabowo, H., Gaol, F., Isa, S. (2024). System development for enhancing social media advertisement engagement through xlnet-based personality classification. Eastern-European Journal of Enterprise Technologies, 4 (2 (130)), 40–51. https://doi.org/10.15587/1729-4061.2024.310375*

1. Introduction

Personalized advertisement is more engaging and effective than generalized advertisement [1]. However, the complex nature of human psychology imposes a challenge in advertisement personalization [2]. Today's digital landscape, characterized by ubiquitous social media platforms, necessitates an in-depth understanding of user psychology for effective marketing. Social media platforms have become pivotal spaces where users share thoughts, feelings, and opinions, revealing their psychological types through their posts. The relevance of this scientific topic is underscored by the increasing dependence of marketing strategies on personalized content, which has been shown to significantly enhance user engagement and conversion rates. This approach uses the hidden sentiments of content social media users post on social media using an Autoregressive Transformer named XLNet [3]. Based on the prediction of the XLNet, it delivers relevant advertisements which align with the personalities of the users. It is an innovative method of combining the sentiment of social media posts with Deep Learning (DL) technology to predict the type of psychology of the users and increase the effectiveness of advertisements by personalizing them according to the prediction.

An innovative autoregressive transformer-based model network optimized for learning from the myPersonality dataset and predicting the psychology types has been developed in this paper [4]. The challenges of processing the myPersonality dataset and converting it into vectors while handling the variable length issues have been overcome in this paper. As a result, the XLNet gains the capability of processing 1500 tokens at a time and predicting the Big 5 Personality traits accurately. Moreover, the personality classifier developed in this paper has been experimented with in a real-world-like test environment, demonstrating that it effectively increases the advertisement impression. Therefore, research devoted to the development of advanced personality classification models for personalized advertising is highly relevant and necessary.

The unique contributions of this paper are listed below:

– effective application of XLNet in developing social media advertisement personalization system using an autoregressive transformer;

– improving the advertisement impression rate by 24 %;

– gaining an impressive accuracy of 97.63 % with 0.95 precision, 0.94 recall, and 0.94 F1-score.

Therefore, research devoted to the development of advanced personality classification models for personalized advertising is highly relevant and necessary. Such research not only enhances our understanding of user behavior and psychology but also drives innovations in digital marketing strategies. By leveraging cutting-edge AI technologies like XLNet, it is possible to create more engaging and effective advertisements that resonate with users on a deeper psychological level. This alignment between user interests and advertisement content leads to higher engagement rates, improved user experiences, and ultimately, more successful marketing outcomes. Hence, continuous exploration and development in this area are imperative for advancing the field of personalized advertising.

2. Literature review and problem statement

The review by [5] suggests that personality trait classification from textual content is a vibrant and evolving research field. This study highlights the value of research in this domain by demonstrating the potential of personality trait classification in understanding user behaviour. [5] provides a strong foundation for the importance of personality trait classification, making a compelling case for further exploration in this area. However, the study does not address the practical challenges associated with implementing personality classifiers at scale, particularly within dynamic environments like social media. The lack of discussion on the real-world applicability of these classifiers creates a gap in understanding their practical utility.

The study [6] emphasizes the importance of personality-related research and demonstrates the effectiveness of the myPersonality dataset in personality classification. This work contributes valuable insights into the robustness and reliability of the myPersonality dataset, confirming its suitability for psychological analysis. Despite these strengths, the study falls short by not applying the classifier to innovative or practical solutions, limiting its impact on real-world applications. The absence of an application domain for the classifier leaves its practical relevance unexplored.

According to [7], the myPersonality dataset contains unbiased social media content, making it an appropriate choice for developing a personality classifier. The study validates the myPersonality dataset as a credible and unbiased source for personality classification, which is crucial for the accuracy and generalizability of the resulting models. However, [7] does not explore any potential application domains for the classifiers, which limits the study's contribution to practical research fields such as marketing or user experience design.

The work by [8] identifies unresolved issues related to the scalability and practical implementation of personality classification systems, pointing out the complex nature of data preprocessing and the need for large computational resources. This study is significant for its identification of key challenges in the practical deployment of personality classifiers, particularly concerning scalability and the computational demands of data preprocessing. However, [8] does not propose concrete solutions to these challenges, leaving a gap in the literature regarding how to effectively scale these systems for broader use.

Machine learning approaches to classify personality traits from the myPersonality dataset represent a well-developed research branch, as highlighted by [9]. This work contributes to the growing body of literature by showcasing the technical advancements in machine learning (ML) for personality classification. However, the study falls short in exploring the practical application domains of these ML-based solutions, leaving their potential in real-world contexts under-explored.

The sentiment-aware deep learning (DL) approach for personality detection developed by [10] demonstrates the effectiveness of DL algorithms in this field. The study provides robust performance metrics, highlighting the technical viability of DL approaches for personality classification. Despite its technical achievements, the study does not extend its findings to practical applications, such as personalized marketing or user experience enhancement. This limits its relevance to applied research.

Similarly, [11] explores a deep learning approach to personality prediction using multiple data sources, highlighting the potential of these algorithms. The study makes a significant contribution by exploring the integration of multiple data sources for personality prediction, which enhances the accuracy and robustness of the results. However, the focus on technical implementation without discussing practical applications limits the study's utility, as it does not address how these predictions can be used in real-world scenarios.

The study by [12] presents a comprehensive analysis of deep learning models for personality trait measurement, contributing valuable insights into their accuracy and efficiency. This work offers a thorough evaluation of DL models, providing important benchmarks for accuracy and efficiency in personality classification. Nonetheless, the study fails to explore the practical applications of these models, such as in personalized marketing, which limits its relevance to applied research domains.

[13] proposes an innovative model for predicting personality behavior from social media data, demonstrating practical feasibility. The study stands out for its innovative approach to using social media data for personality prediction, highlighting the potential for practical applications in various fields. However, the study does not adequately address the ethical and privacy implications of using social media data, which is a critical oversight in real-world applications.

The critical analysis of these studies reveals that while deep learning algorithms have been successfully applied to personality classification, there is a common limitation in the literature: the integration of these classifiers into practical applications has not been thoroughly explored. Most research, including that by [14], focuses on developing classifiers without considering their application domains, thereby limiting their practical applicability.

The effectiveness of personalized advertisements has been studied extensively. For example, [15, 16] evaluated such systems using a confusion matrix but did not assess real-world impacts. This study provides a methodological approach to evaluating personalized advertisements, offering insights into their effectiveness in controlled environments. However, the lack of real-world impact assessment limits the study's applicability, as it does not account for the dynamic nature of consumer behavior in actual marketing scenarios.

Similarly, [17] explored the field without assessing real-world impacts, highlighting the challenges due to the dynamic nature of consumers. The study acknowledges the complexity of consumer behavior, which is essential for understanding the challenges in personalized marketing. Yet, it fails to propose effective solutions for adapting personalized advertisements to these dynamic conditions, limiting its practical relevance.

According to [18], the variety of consumers makes advertisement personalization challenging, a sentiment echoed by [19]. Both studies contribute to the understanding of the inherent challenges in personalizing advertisements for a diverse consumer base, providing valuable insights into the complexities of this task. However, they do not propose concrete methods for overcoming these challenges, leaving a gap in the literature regarding the practical implementation of personalized marketing strategies.

[20] examined these challenges from an AI perspective but did not propose effective solutions for real-time data processing and personalization at scale. The study provides an AI-centric analysis of the difficulties in real-time data processing for personalized advertising, contributing to the theoretical understanding of these challenges. However, the lack of proposed solutions leaves the study without practical impact, as it does not address how to overcome the identified obstacles. All this suggests that it is advisable to conduct a study on the integration of efficient personality classification with practical advertisement personalization systems.

3. The aim and objectives of the study

The aim of the study is to develop an effective and scalable social media advertisement personalization system using autoregressive transformer-based personality classification.

To achieve this aim, the following objectives are accomplished:

– to develop a robust personality classification model using the myPersonality dataset and XLNet;

– to implement and evaluate the personality classification model in a real-world-like test environment to personalize advertisements based on user personalities.

4. Materials and methods research

The focus of this study is the development and evaluation of a social media advertisement personalization system that leverages advanced personality classification techniques, specifically using the XLNet model. The primary aim is to determine whether accurately classifying user personalities based on the Big 5 OCEAN traits can significantly enhance user interaction rates with personalized advertisements compared to more generalized advertising approaches.

To explore this, the study operates under several key assumptions. First, it is assumed that the myPersonality dataset, which forms the basis of the training data, is representative of the broader social media user population and accurately reflects users' personality traits. Additionally, the study presupposes that the established correlations between personality traits and advertisement preferences, as highlighted in existing literature, are applicable to the users within the experimental framework. Another critical assumption is that the XLNet model, after being trained on the myPersonality dataset, will maintain its high accuracy when applied to real-world social media data. Finally, it is assumed that user interactions with personalized advertisements will primarily be influenced by how well the content aligns with their classified personality traits.

To ensure the feasibility of the research, several simplifications were adopted. The study focuses exclusively on the Big 5 OCEAN personality traits, omitting other possible classification frameworks. Additionally, only social media posts of up to 1500 tokens were considered, which simplified data processing but may exclude more complex posts. The experimental environment utilized simulated users and social media profiles, acknowledging that this setup might not fully capture the behavior of actual users in a real-world context. Lastly, the study assumes uniformity in user internet behavior, without accounting for potential cultural or regional differences that could affect advertisement interactions.

The dataset analysis involves inspecting the structure of the dataset, studying the metadata, and understanding the dataset structure [21]. The dataset processing starts with missing data management. After that, the texts are normalized by lowercasing the letters, handling special characters and missing values, and removing stopwords. Then, the words are tokenized, vectors and sequences are formed, and the dataset is split. The overall process is illustrated in Fig. 1 [22]:

1. Dataset description. The myPersonality dataset developed by [23] has been used in this paper, resulting from an experiment conducted at the University of Cambridge. Participants of this research project volunteered for a personality test, which allowed the researchers to access their social media data. In this research project, 10,000 social media posts were collected and later correlated with the users' personalities. The five-factor theory of personality coined by [24] has been used in this study to categorize personalities. It is also known as the Big Five Personality Traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism [25]. It is known as the OCEAN personality type [26]. A dataset sample has been listed in Table 1.

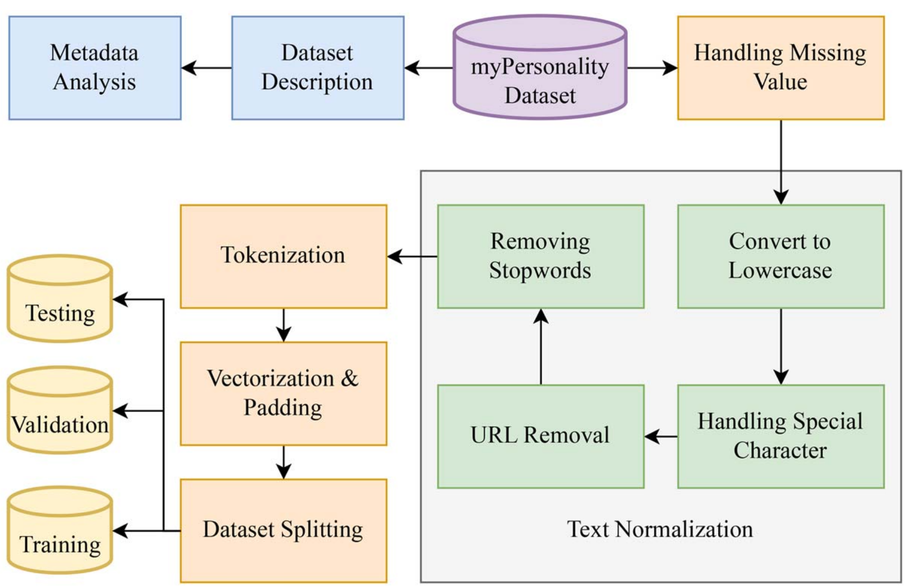


Fig. 1. The flowchart of the dataset analysis and processing

Table 1

Social media posts and corresponding big five personality traits

Status Content	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Just finished reading an amazing book on artificial intelligence and its future impact on society! Its good how technology is changing and reshaping our world. Can't wait to learn more about new tech next	0.85	0.6	0.8	0.7	0.35
Big day tomorrow! Need prayers! Well prepared but need luck to survive. Wish me luck guys! Cheeeers!	0.6	0.85	0.55	0.6	0.5
Exploring new places always brings so much joy and inspiration! Just returned from a hiking trip in the mountains, and the views were absolutely breathtaking. Looking forward to planning my next adventure	0.9	0.5	0.7	0.65	0.45
Enjoying a quiet evening with a cup of coffee and a good book. There's something so calming about these peaceful moments after a busy day. Grateful for the small joys in life	0.55	0.85	0.4	0.75	0.3
Starting to plan a new project for the next quarter at work! It's always exciting to brainstorm new ideas and set fresh goals. I'm looking forward to working with the team and seeing what we can achieve	0.7	0.8	0.65	0.8	0.4

2. Missing data management. During the myPersonality dataset analysis, several irrelevant instances have been discovered and removed. It introduced a missing value problem. The dataset is defined as a collection of text T where, $T=\{t_1, t_2, ..., t_N\}$ with N entries. Some t_i are missing or too short to be considered proper social media content. These values have been removed using the mathematical condition expressed in (1) [27].

$$t_i' = \begin{cases} t_i, \text{ if } t_i \text{ is not missing,} \\ \text{mode}(T) \text{ or } t_{placeholder}, \text{ if } t_i \text{ is missing.} \end{cases} \quad (1)$$

3. Normalizing the texts. The social media content on the myPersonality dataset has been normalized by converting the capital letters into small letters, as this variation does not contribute to the meaning but introduces complexities in the feature vector. The special characters and Uniform Resource Locators (ULRs) have also been removed. Finally, the stopwords have been removed in the text normalization process [28]:

a) Converting to lowercase. Every word defined by v_k in (2) is processed by the function M: String→String. It converts any capital letter available in the world into a small letter. This process does not affect the meaning of the text. However, it simplifies the feature vectors:

$$M(v_k) = \text{lowercase}(v_k), \quad \forall k \in [1, m_l], \forall l \in [1, L]; \quad (2)$$

b) Handling special characters and URLs: The myPersonality dataset analysis reveals the presence of special characters and URLs in the sample posts, which play no role in the classification. As a result, they have been removed from the dataset. The removal process is governed by (3) where a bespoke function F: String→String has been implemented, with its operational logic delineated in the ensuing equation:

$$F(v_k) = \text{eliminate\_elements}(v_k),$$

$$\forall k \in [1, m_l], \forall l \in [1, L]; \quad (3)$$

c) Removing stopwords. In an effort to streamline the feature space, stopwords were excluded from the myPersonality dataset, effectively reducing feature dimensionality. Stopwords, which provide a minimal contribution to textual meaning and context, consist of commonly used words in English that detract from the analytical focus on critical elements. Recognized as a potent strategy for feature optimization in natural language processing, the exclusion of stopwords significantly enhances the analytical clarity of the dataset. The set comprising all identified stopwords in English is represented by R, and the function F: String→String is defined to purge these stopwords from any text s_i, as per (4):

$$F(s_i) = [u_k u_k \notin R], \quad \forall i \in [1, M]. \quad (4)$$

The overall normalization process utilized in this study is described through a concise function, where M delineates the operation, and s_i is the i-th text sample. The overall process is expressed in (5):

$$M(s_i) = F(G(H(s_i))), \quad \forall i \in [1, M]. \quad (5)$$

4. Tokenization. The normalized dataset is ideal for tokenization, an essential step in processing the data for the proposed XLNet. The given text sample S is dissected into an array of discrete elements, either words or subwords. This procedure is governed by (6), wherein ϕ denotes the tokenization operation [29]:

$$\phi(S) = [s_1, s_2, \ldots, s_n], \quad \forall n \le m. \quad (6)$$

5. Vectorization & sequence padding. The XLNet requires vectorized sequences of tokens to learn from the features of the myPersonality dataset. In this paper, the token u and a corresponding word embedding ψ, each token gets associated with a vector within Rn, where n represents the embedding space's dimensionality. This relationship is articulated through (7) [30]:

$$\psi(u) \in R^n. \quad (7)$$

After forming the word vector, the text sequences are transformed into a sequence expressed as $\xi(s)=[u1, u2, ..., um]$ The procedure for converting these sequences into a series of vectors accommodating multiple input tokens is defined by (8):

$$Z=\left[\psi(u_1),\psi(u_2),\ldots,\psi(u_m)\right]. \quad (8)$$

Given the variable lengths of vectors as presented in (8), a consistent input size is required for XLNet functionality. This paper employs sequence padding to address discrepancies in vector lengths. Through this method, each vector sequence Z is either extended or shortened to a uniform length M, utilizing zero-padding vectors in Rn as per the (9):

$$\text{Standardize}(Z,M)=\begin{cases} Z \,\|\left[O_{pad},O_{pad},\ldots\right], & x<0, \\ Z[1:M], & x\geq 0. \end{cases} \quad (9)$$

6. Dataset splitting. The original myPersonality dataset comprises 10,000 instances. Following the dataset's preparation, it consists of 9926 items. The dataset has been split into training, testing, and validation segments by maintaining a ratio of 70 %, 15 %, and 15 %, respectively. After splitting, there are three datasets. The data instances were randomly shuffled during the splitting to ensure proper diversity in each dataset. After splitting, there are 6948 instances in the training dataset. Both testing and validation sets have 1488 instances each:

6. 1. Personality and advertisement correlation.

How social media users engage with content strongly correlates with their personality [27]. Studies show that the advertisement individuals prefer has an interconnection with their personalities [28, 29]. These interconnections have been listed in Table 2.

Table 2

The relation among different personality traits and types of advertisement they prefer

Big five personality trait	Trait description	Preferred types of advertisement
Openness to experience	Imaginative, open to new ideas, and interested in novelty	Innovative and creative content
		Inspirational and informative ads
		Interactive and engaging ads
Conscientiousness	Organized, responsible, and goal-oriented	Detailed and informative ads
		Professional and reliable products
		Ads emphasizing planning and order
Extraversion	Sociable, outgoing, and energetic	Social and engaging ads
		Lively and exciting ads
		Influencer endorsements
Agreeableness	Trusting, altruistic, and cooperative	Charitable and ethical ads
		Positive and friendly ads
		Family and relationship-focused ads
Neuroticism	Emotionally unstable, anxious, and sensitive	Reassuring and comforting ads
		Ads offering solutions to problems
		Security and stability-focused ads

6. 2. XLNet architecture.

The XLNet has been used in this paper as the personality classifier. It is an autoregressive transformer model used in Natural Language Processing (NLP) tasks [3]. The proposed system intends to classify social media user personality and, based on that, personalize the advertisement. That is why XLNet is a good fit for the task. It has been trained on the myPersonality dataset containing the social media content of various users. The experimenting XLNet accepts 512 tokens as input. The token sequence is expressed as $z=[z_1, z2, ..., z_n]$. There are two special tokens [CLS] and [SEP] included, as shown in (10):

$$z=\left[[\text{CLS}],z_1,z_2,\ldots,z_m,[\text{SEP}]\right]. \quad (10)$$

The input layer passes the input tokens to the embedding layer. In the proposed social media advertisement personalization system, the size of the embedding layer was set to 1024. The embedding layer produces dense vectors from the token. The process of this conversion is described by the formula in (11), where $\mathrm{v}_{z_i} \in R^{d_{model}}$:

$$V(z)=\left[v_{[\text{CLS}]},v_{z_1},v_{z_2},\ldots,v_{z_m},v_{[\text{SEP}]}\right]. \quad (11)$$

The data are transferred to the transformer layers after embedding the input tokens and converting them into dense vectors. The autoregressive transformer model used in this paper has 12 stacked transformer layers. Each of these layers contains a multi-head self-attention mechanism and a feed-forward network. The attention head is denoted by a and defined by Equation (12):

$$\text{Attention}(Q,K,V)=\text{softmax}\left(\frac{QK^{\top}}{\sqrt{d_k}}\right)V. \quad (12)$$

In (12), $Q=ZW_Q$, $K=ZW_K$, and $V=ZW_V$. The model utilizes 16 attention heads, each with a dimension of 64. The purpose is to produce a Multi-Head Attention. It is done by concatenating and projecting the attention heads. The processing is governed by (13), where $\text{head}_i=\text{Attention}(Q, K, V)$:

$$\text{MultiHead}(Q,K,V)=\text{Concat}(\text{head}_1,\ldots,\text{head}_H)W_O. \quad (13)$$

After the Multi-Head Attention layer processes the data, they are transmitted to a fully connected network called Feed Forward Network (FFN). It performs two linear transformations. The ReLU activation function has been used here to process the signals. The entire process follows the mathematical principle expressed in (14):

$$\text{FFN}(x)=\max(0,xW_1+b_1)W_2+b_2. \quad (14)$$

In (14), $W_1\in R^{d_{model}\times d_{inner}}$ and $W_2\in R^{d_{inner}\times d_{model}}$. The lengths of social media content vary depending on multiple factors and are non-deterministic. Extracting features from longer posts is more complicated than shorter posts. Segment-level recurrence was used in this study to ensure that XLNet can proficiently capture long-term dependencies. This process follows the mathematical structure of (15) where h^l denotes the hidden state of the l-th layer and c represents the context. Subsequently, relative positional encoding is added to provide positional information to the embeddings, as described in (16), where i and j are token positions within the sequence:

$$h^l=\text{SegmentRecurrence}\left(h^{l-1},c\right), \quad (15)$$

$$v_{\text{pos}}(i,j) = \text{Embed}_{\text{pos}}(i-j). \quad (16)$$

The representations from the embedding layer require aggregation before proceeding to the final dense layer. A pooling layer expressed in (17) performs the aggregation. In this process, L is the total number of transformer layers. After aggregation, the data are transferred to the dense layer. In the dense layer, the softmax activation function has been used. It is defined in (18). It classifies the input into one of the 16 classes:

$$h_{[\text{CLS}]} = \text{Pooling}\left(h^L_{[\text{CLS}]}\right), \quad (17)$$

$$P = \text{softmax}\left(Wh_{[\text{CLS}]} + b\right). \quad (18)$$

In (18), $W \in R^{d_{\text{model}} \times d_{\text{num}}}$ classes and $b \in R^{d_{\text{num}}}$ classes. The different layers of the XLNet architecture used in this study, along with their descriptions and parameters where applicable, are summarized in Table 3.

Table 3

Description and parameters of XLNet architecture layers

Layer	Description	Parameters
Input layer	Receives the input tokens and passes them to the next layer	Seq length: 512
Embedding layer	Produces dense vector from input tokens	Emb size: 1024
Transformer layers	Responsible for multi-head attention and the FFN	Layers: 12
Multi-head attention	Performs the computation of attention scores	Heads: 16, Head size: 64
Feed-forward network	Transform the input data using the ReLU activation function	Inner size: 4096
Segment recurrence	Captures long-term dependencies from text data	NA
Positional encoding	Processes and adds positional information	NA
Pooling layer	Aggregates the data from embedding layer	NA
Classification layer	Classifies the input into one of the 5 classes	Output: 5 classes

Fig. 2 illustrates the learning progression of XLNet, which was utilized in this study to develop the proposed social media advertisement personalization system using autoregressive transformer-based personality classification. It shows that the network is trained correctly. The scale of observation has been presented in decimal points so that the oscillation of the learning curve is properly visible. In the numerical scale, the distances between the training and validation curves are marginal, which indicates that the learning process didn't overfit.

6. 4. Advertisement personalization algorithm.

The proposed social media advertisement personalization system uses the autoregressive transformer, XLNet, to classify the personality of the social media users. Based on the classification, the personalized advertisement is delivered. The advertisement personalization algorithm presented as Algorithm 1 controls the entire process. The process is illustrated in Fig. 3.

The process starts with the customer database query, where customers' information, including their social media profile URLs, is available. The query retrieves the social media profile of the target customer, and the profile URL goes to the Social Media Scraper. The scraper accesses the profile, retrieves the HTML page, inspects the tags, and stores the posts in arrays. These arrays are then transferred to the Data Processing module. This module normalizes the text, tokenizes them, converts them into vectors, and performs sequence padding. After that, the vectorized word sequences are passed to the XLNet. It predicts the personality. Based on this prediction, the advertisement is designed and delivered. Table 4 shows the workflow in a pseudo-code form.

Table 4

Advertisement personalization algorithm

Algorithm 1: advertisement personalization algorithm
1. Input: customer database D, profile URLs $\{URL_i\}$
2. Output: personalized advertisement, A
3. Procedure PERSONALIZEAD
4. For each customer i do
5. Query $D \rightarrow URL_i$
6. Scrape $URL_i \rightarrow P$
7. $P \rightarrow V$ ► Normalize, tokenize, vectorize
8. XLNet(V) $\rightarrow P_{\text{pe}}$
9. $P_{\text{pe}} \rightarrow A$ ► Design ad
10. Deliver A
11. end for
12. end procedure

The proposed system's performance has been evaluated from two perspectives. First, the performance of the personality classifier has been analyzed. Later, an experimental environment has been created to explore the proposed system's performance. It reflects the characteristics of real-world settings.

Evaluation metrics.

The proposed social media advertisement personalization system uses an autoregressive transformer to make decisions based on personality classification. The literature review suggests that accuracy, precision, recall (sensitivity), and F1 Score are widely used evaluation metrics to evaluate the performance of Deep Learning (DL) models. These values are calculated using True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), which are obtained from the confusion matrix. These evaluation metrics are defined by (19)–(22), respectively:

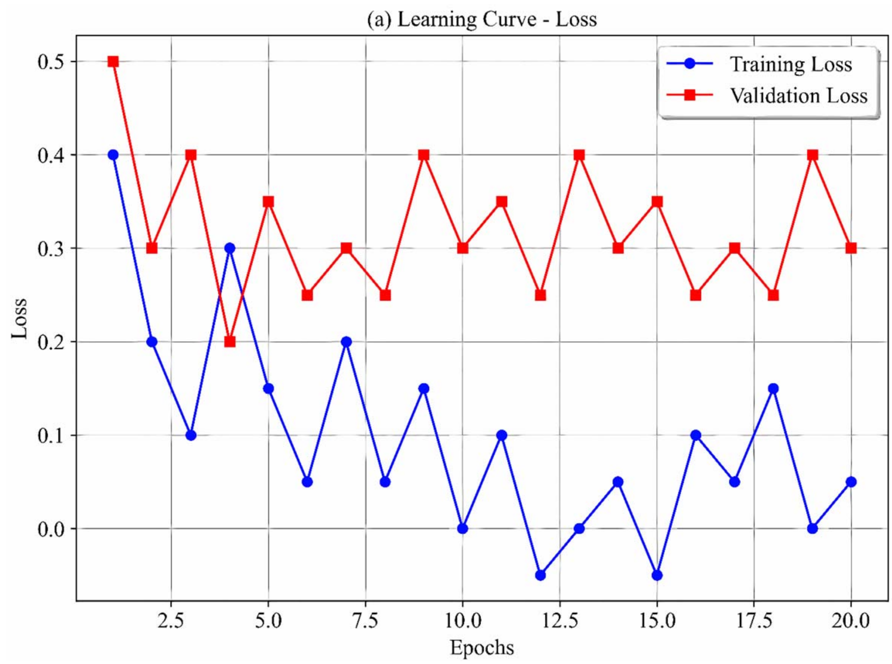
$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}, \quad (19)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad (20)$$

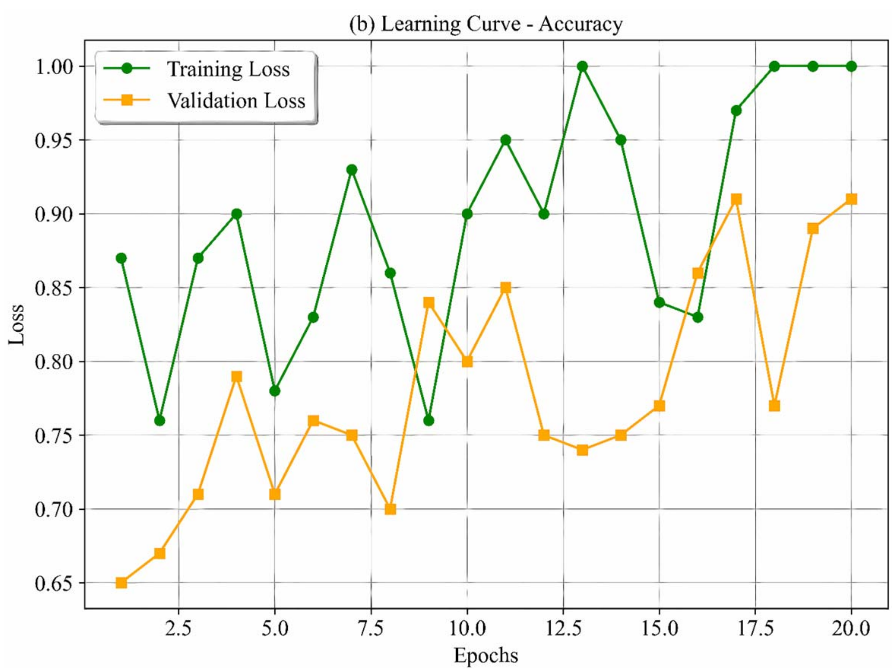
$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \quad (21)$$

$$\text{F1 Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}. \quad (22)$$

These metrics provide a comprehensive evaluation of the model's performance. Accuracy measures the overall correctness of the model, precision assesses the proportion of positive identifications that were actually correct, recall indicates the model's ability to identify positive instances, and the F1 Score provides a balance between precision and recall. Together, these metrics ensure a thorough assessment of the model's classification capabilities, highlighting both its strengths and areas for improvement.



a



b

Fig. 2. The learning curve of the XLNet model trained for this study's proposed system: *a* – the loss curve; *b* – the accuracy curve

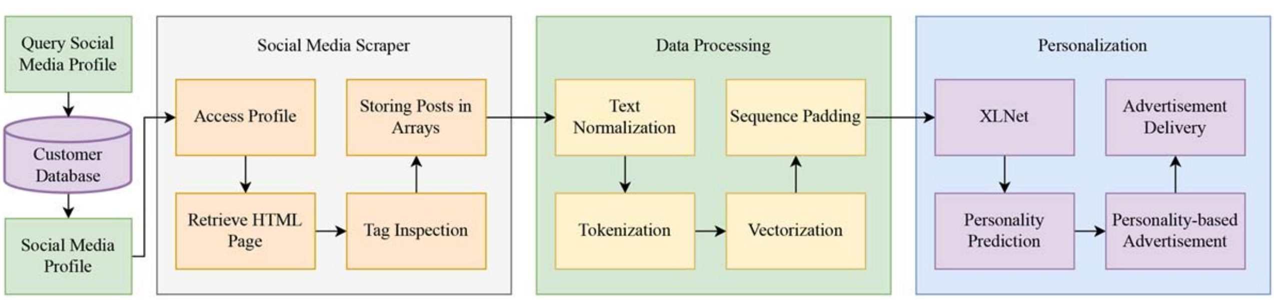


Fig. 3. The workflow of proposed social media advertisement personalization

5. Results of performance evaluation of the XLNet-based advertisement personalization system

5. 1. Development of a robust personality classification model

The confusion matrix of the XLNet's performance in classifying the five classes is illustrated in Fig. 4. It shows that the overall accuracy is over 96 % for every personality trait. The precision of the model doesn't fall below 0.94. That means the proposed classifier is efficient in minimizing false positives. The recall values exceed 0.92 for every class. It indicates the classifier's strength in identifying true instances of each trait. The range of F1-score is 0.93 to 0.96. It reflects a balanced performance between precision and recall. That means the classifier can provide both accurate and extensive coverage of personality traits. The data on the confusion matrix strongly supports the classifier's efficacy in accurately classifying the personality traits of social media users according to their social media content.

The overall classification performance on the test dataset is listed in Table 4. There are 1488 instances in this dataset. According to XLNet's prediction, there are 281 TPs, 1174 TNs, 14 FPs, and 19 FNs on average. The average classification accuracy is 97.63 %. The average precision, recall and F1-score values are 0.95, 0.94, and 0.94, respectively. These data indicate excellent performance of the XLNet-based personality classification system.

The k-fold cross-validation results are presented in Table 5 for k=5.

Table 5 demonstrates the classifier's consistent and robust performance across multiple validation sets. With accuracy values consistently exceeding 96.8 % and an overall average of 97.47 %, the classifier shows high reliability in predicting the Big Five personality traits. Precision and recall metrics, hovering around 0.95 and 0.94 respectively, indicate a balanced ability to correctly identify and classify each trait while minimizing false positives and negatives. The F1-score, which harmonizes precision and recall, consistently remains at 0.94, reflecting the model's efficiency and stability in real-world applications. Fig. 5 further validates the consistency of the classifier in accurately classifying the personality at different dataset settings.

Table 4

Classification metrics for big five personality traits

Class	TP	TN	FP	FN	Accuracy (%)	Precision	Recall	F1-Score
Openness	283	1176	12	17	98.06	0.96	0.94	0.95
Conscientiousness	280	1174	14	20	97.59	0.95	0.93	0.94
Extraversion	287	1178	10	13	98.52	0.97	0.96	0.96
Agreeableness	278	1173	15	22	97.18	0.95	0.93	0.94
Neuroticism	275	1171	17	25	96.78	0.94	0.92	0.93
Average	281	1174.4	13.6	19.4	97.63	0.95	0.94	0.94

Table 5

The performance validation through k-fold cross validation at k=5

k-fold	Accuracy (%)	Precision	Recall	F1-Score
1	0.975	0.95	0.94	0.94
2	0.9765	0.95	0.94	0.95
3	0.968	0.94	0.93	0.93
4	0.9795	0.96	0.95	0.95
5	0.9745	0.95	0.94	0.94
Average	97.47	0.95	0.94	0.94

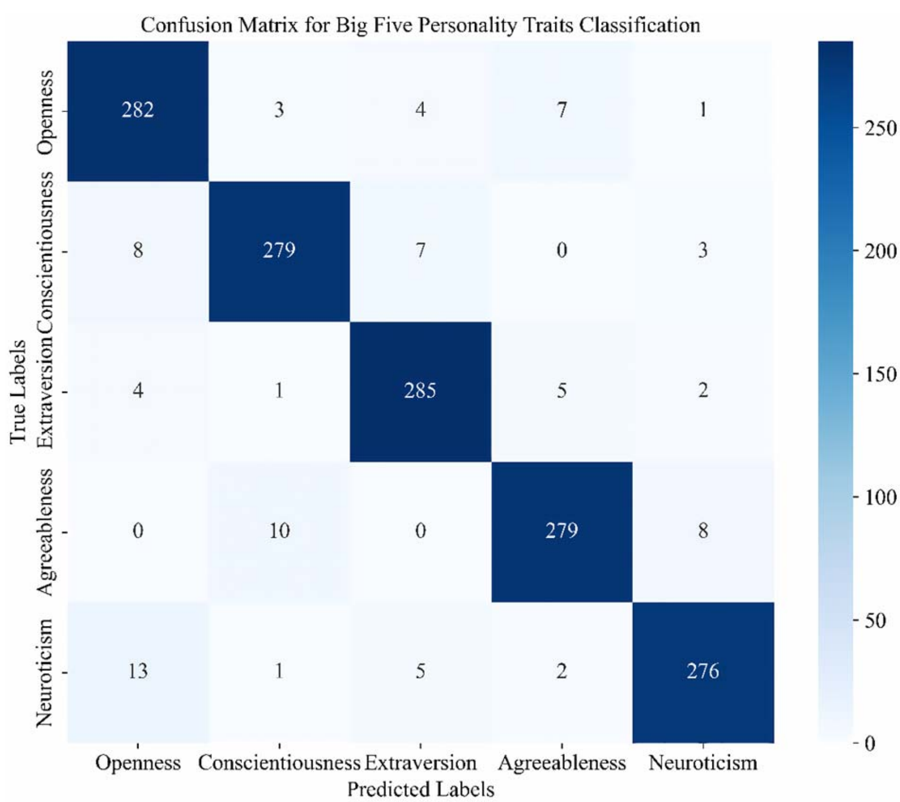


Fig. 4. The confusion matrix analysis of the personality classification

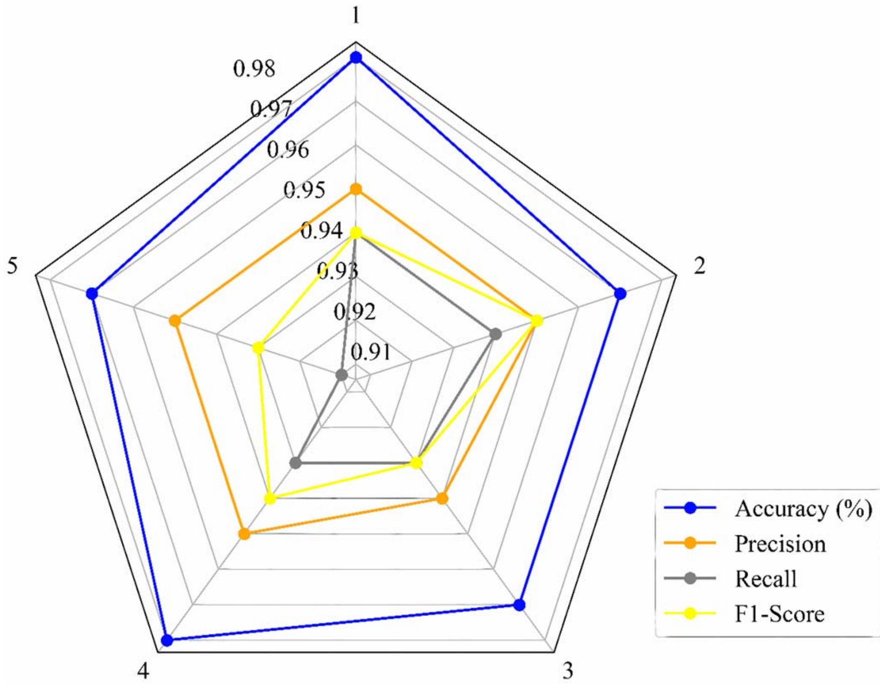


Fig. 5. Performance validation through k-fold cross validation

Fig. 5 as seen above, shows consistency across all folds validates the classifier's effectiveness. This underscores the study's results practical utility in accurately identifying personality traits from diverse data sets.

5. 2. Implementation and evaluation in a real-world-like test environment

Table 6 presents the data obtained from the experimental setup where the proposed Social Media Advertisement Personalization system has been applied.

According to the findings, a user with an Openness personality experienced an increase from 3 to 9 interactions. That means it is a 40 % improvement. Similarly, an Agreeableness user saw a rise in interactions from 2 to 11, showing a 60 % improvement. On average, personalized advertisements led to a 24 % increase in interactions compared to generalized advertisements. This demonstrates that by tailoring content to match users' personality profiles, the system significantly boosts user engagement, validating its efficacy in creating more engaging and user-centric advertising experiences:

1. Permission dependent.

The system requires the permission of the customers to analyze their social media profiles. If the permission is not granted, it goes beyond the legal boundaries of the proposed system. It is a significant limitation of it. A well-defined user agreement with the assurance of privacy solves this problem. However, it has not been addressed in this paper and will be explored in the future scope of this research.

2. Post length limitation.

The system fails to process social media posts with more than 1500 tokens. Although this is appropriate for the myPersonality dataset, it may not be appropriate for all datasets. Sometimes, social media posts are longer than 1500 tokens can accommodate. This is another system limitation. This limitation will be overcome in the subsequent version of the proposed system.

Table 6

Performance of the proposed system in experimental settings

User	Actual personality	Predicted personality	Browsing duration (minutes)	Generalized advertisement		Personalization advertisement		Interaction improvement
				Number	Interaction	Number	Interaction	
1	Openness	Openness	69	15	3	15	9	40.00
2	Agreeableness	Agreeableness	51	15	2	15	11	60.00
3	Neuroticism	Neuroticism	59	15	5	15	4	–6.67
4	Agreeableness	Agreeableness	79	15	5	15	5	0.00
5	Neuroticism	Neuroticism	78	15	6	15	10	26.67
6	Agreeableness	Agreeableness	76	15	7	15	11	26.67
7	Extraversion	Extraversion	45	15	5	15	11	40.00
8	Extraversion	Extraversion	86	15	4	15	8	26.67
9	Neuroticism	Neuroticism	69	15	5	15	6	6.67
10	Conscientiousness	Conscientiousness	76	15	6	15	9	20.00
Average			68.8	15	5	15	8	24.00

3. Experimental setup.

The proposed system has been experimented with in a test environment. The customers in the test environment are not real customers, another major limitation of the paper. However, these dummy customers behave as real customers, which justifies the experimental analysis. Yet, a real-world performance analysis is essential, which will be explored in the future scope of this research.

The limitations of this paper pave the way for further research, improving the system's performance and capability and making it a robust and efficient system for advertisement personalization.

6. Discussion of the results of the study on XLNet-based advertisement personalization

The results of this study demonstrate that the autoregressive transformer-based model, specifically the XLNet, can effectively classify user personalities based on social media posts and subsequently personalize advertisements. The high classification accuracy (97.47 %) and improved advertisement interaction rates (24 % improvement) can be attributed to the robustness of the XLNet model and the comprehensive preprocessing of the myPersonality dataset, as illustrated in Table 4 and Fig. 4. The model's ability to process up to 1500 tokens at a time allows it to capture long-term dependencies in the text, which enhances the accuracy of personality classification. The results shown throughout the article support these results by showing the high precision, recall, and F1-scores across different personality traits.

The performance comparison of the proposed results with existing papers is listed in Table 7. The research gap in exploring the application domain is also highlighted in this table.

Table 7

Performance comparison among different papers of section 2 with the proposed paper

Paper	Accuracy	Precision	Recall	F1-Score	Application
[6]	74.17 %	NA	NA	NA	Ignored
[8]	74.2 %	NA	NA	NA	Ignored
[9]	72.69 %	67.79 %	73.44 %	68.68 %	Ignored
[11]	87.89 %	NA	NA	92.4 %	Ignored
[14]	86.31	NA	NA	86.08	Ignored
Proposed	97.47 %	95 %	94 %	94 %	Advertisement

The proposed system, as seen from Table 7, shows a significant improvement across all metrics compared to other papers reviewed in this study. These improvements can be directly attributed to several key innovations in the design and implementation of the XLNet-based model.

Unlike models used in previous studies, such as those in [6, 8, 9], which relied on traditional machine learning approaches or earlier deep learning architectures, XLNet introduces a number of significant advancements. The autoregressive nature of XLNet allows it to better capture long-term dependencies within text, which is crucial for accurately modeling personality traits from social media content. This ability to process up to 1500 tokens at a time ensures that the model can effectively handle longer, more complex inputs without losing contextual information, a common limitation in earlier models.

Additionally, the superior performance in precision, recall, and F1-score observed in our study can be linked to the optimization techniques specifically tailored to the myPersonality dataset. For instance, the application of advanced preprocessing techniques, including the handling of missing data and normalization, contributed to the robustness of the model's predictions. These aspects were either not fully addressed or were handled less effectively in the previous studies, as evidenced by their lower performance metrics.

These outcomes indicate that the developed system not only achieves high accuracy in personality classification but also significantly enhances user engagement in social media advertisement personalization. This research thus provides a viable and scalable solution for integrating personality classification into practical marketing applications, addressing existing gaps and paving the way for future innovations in personalized advertising.

The novelty of this results is further highlighted by the application of the personality classification model for the context of advertisement personalization, which has not been done in previous studies. Unlike previous works, such as [10], which focused on sentiment-aware deep learning approaches without extending the application to practical domains, our study integrates personality classification with advertisement personalization. This integration not only bridges the gap between theory and application but also demonstrates a clear practical impact through the observed increase in advertisement interaction rates.

The high classification accuracy and improved interaction rates translate directly into practical benefits for social media advertising. By delivering personalized advertisements that align closely with the user's personality traits, the proposed system enhances user engagement, which is a critical metric in digital marketing. This practical outcome is a clear demonstration of the advantages of using advanced NLP models like XLNet in real-world applications, something that earlier studies, which largely remained theoretical, failed to achieve.

While the proposed system demonstrates significant improvements over previous models, it does have its limitations, primarily related to the reliance on the myPersonality dataset, which may not represent all types of social media content or user demographics. The lack of diversity in the dataset limits the system's generalization capability. Furthermore, the system's ability to handle social media posts longer than 1500 tokens is restricted, which could result in incomplete personality assessments for longer posts.

Future research should focus on expanding the dataset to include a more diverse range of social media content and user demographics. Additionally, exploring the integration of additional contextual information, such as user browsing history and real-time behavior, could further enhance the accuracy and relevance of personalized advertisements. Addressing privacy concerns through advanced data anonymization techniques and secure data handling practices will also be crucial for the practical application of this system.

7. Conclusions

1. The study developed a robust personality classification model using the myPersonality dataset and XLNet. The model achieved a remarkable classification accuracy of 97.47 %, with precision, recall, and F1-scores of 0.95, 0.94, and 0.94, respectively. These quantitative indicators demonstrate the high effectiveness and reliability of the personality classification model.

2. The personality classification model was implemented and evaluated in a test environment reflecting real-world social media characteristics. The experimental results showed a 24 % increase in user interaction after using the XLNet-based personality classification for advertisement personalization. This significant improvement in engagement indicates the system's practical applicability and effectiveness in enhancing social media advertisement engagement. The study also addressed critical challenges in data preprocessing, including handling variable text lengths and missing values, ensuring the robustness of the personality classification model. By overcoming these challenges, the proposed system demonstrates its potential for practical application in real-world marketing strategies, providing a scalable solution for personalized advertisement delivery.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

This paper uses the publicly available myPersonality dataset, which is available at the Psychometrics Center of Cambridge Judge Business School of the University of Cambridge: https://www.psychometrics.cam.ac.uk/productsservices/mypersonality.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

References

1. Kim, J. (Jay), Kim, T., Wojdynski, B. W., Jun, H. (2022). Getting a little too personal? Positive and negative effects of personalized advertising on online multitaskers. Telematics and Informatics, 71, 101831. https://doi.org/10.1016/j.tele.2022.101831
2. Lindenberger, U., P tter, U. (1998). The complex nature of unique and shared effects in hierarchical linear regression: Implications for developmental psychology. Psychological Methods, 3 (2), 218–230. https://doi.org/10.1037//1082-989x.3.2.218
3. Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R. R., Le, Q. V. (2019). Xlnet: Generalized autoregressive pretraining for language understanding. 33rd Conference on Neural Information Processing Systems (NeurIPS 2019). Available at: https://papers.nips.cc/paper_files/paper/2019/file/dc6a7e655d7e5840e66733e9ee67cc69-Paper.pdf
4. Varma, G. R., Mohan, A., Prasanna, K. C. V. (2024). A robust ensemble model for disposition prediction using the myersbriggstype indicator (MBTI) in machine learning. Advances in Networks, Intelligence and Computing, 335–346. https://doi.org/10.1201/9781003430421-33
5. Ahmad, H., Asghar, M. Z., Khan, A. S., Habib, A. (2020). A Systematic Literature Review of Personality Trait Classification from Textual Content. Open Computer Science, 10 (1), 175–193. https://doi.org/10.1515/comp-2020-0188
6. Tandera, T., Hendro, Suhartono, D., Wongso, R., Prasetio, Y. L. (2017). Personality Prediction System from Facebook Users. Procedia Computer Science, 116, 604–611. https://doi.org/10.1016/j.procs.2017.10.016
7. El-Demerdash, K., El-Khoribi, R. A., Ismail Shoman, M. A., Abdou, S. (2022). Deep learning based fusion strategies for personality prediction. Egyptian Informatics Journal, 23 (1), 47–53. https://doi.org/10.1016/j.eij.2021.05.004
8. Tadesse, M. M., Lin, H., Xu, B., Yang, L. (2018). Personality Predictions Based on User Behavior on the Facebook Social Media Platform. IEEE Access, 6, 61959–61969. https://doi.org/10.1109/access.2018.2876502
9. Serrano-Guerrero, J., Alshouha, B., Bani-Doumi, M., Chiclana, F., Romero, F. P., Olivas, J. A. (2024). Combining machine learning algorithms for personality trait prediction. Egyptian Informatics Journal, 25, 100439. https://doi.org/10.1016/j.eij.2024.100439
10. Suhartono, D., Ciputri, M. M., Susilo, S. (2024). Machine Learning for Predicting Personality using Facebook-Based Posts. Engineering, MAthematics and Computer Science Journal (EMACS), 6 (1), 1–6. https://doi.org/10.21512/emacsjournal.v6i1.10748
11. Sirasapalli, J. J., Malla, R. M. (2023). A deep learning approach to text-based personality prediction using multiple data sources mapping. Neural Computing and Applications, 35 (28), 20619–20630. https://doi.org/10.1007/s00521-023-08846-w
12. Yang, K., Lau, R. Y. K., Abbasi, A. (2023). Getting Personal: A Deep Learning Artifact for Text-Based Measurement of Personality. Information Systems Research, 34 (1), 194–222. https://doi.org/10.1287/isre.2022.1111
13. Samota, H., Sharma, S., Khan, H., Malathy, M., Singh, G., Surjeet, S., Rambabu, R. (2024). A novel approach to predicting personality behaviour from social media data using deep learning. International Journal of Intelligent Systems and Applications in Engineering, 12 (15s), 539–547. Available at: https://ijisae.org/index.php/IJISAE/article/view/4788
14. Maulidah, M., Pardede, H. F. (2021). Prediction Of Myers-Briggs Type Indicator Personality Using Long Short-Term Memory. Jurnal Elektronika Dan Telekomunikasi, 21 (2), 104. https://doi.org/10.14203/jet.v21.104-111
15. Biswas, S., Bhat, S., Jaiswal, G., Sharma, A. (2022). Critical Insights into Machine Learning and Deep Learning Approaches for Personality Prediction. Proceedings of 3rd International Conference on Machine Learning, Advances in Computing, Renewable Energy and Communication, 707–718. https://doi.org/10.1007/978-981-19-2828-4_63

16. Bleier, A., Eisenbeiss, M. (2015). Personalized Online Advertising Effectiveness: The Interplay of What, When, and Where. Marketing Science, 34 (5), 669–688. https://doi.org/10.1287/mksc.2015.0930
17. Abdel Monem, H. (2021). The Effectiveness of Advertising Personalization. Journal of Design Sciences and Applied Arts, 2 (1), 335–344. https://doi.org/10.21608/jdsaa.2021.31121.1061
18. Sathe, A. B., Mane, S. B. (2021). Rethinking Offline Personalized Advertising: Challenges and System Design. International Journal of Computer Applications, 174 (19), 1–6. https://doi.org/10.5120/ijca2021921074
19. Strycharz, J., van Noort, G., Smit, E., Helberger, N. (2019). Consumer View on Personalized Advertising: Overview of Self-Reported Benefits and Concerns. Advances in Advertising Research X, 53–66. https://doi.org/10.1007/978-3-658-24878-9_5
20. Gao, B., Wang, Y., Xie, H., Hu, Y., Hu, Y. (2023). Artificial Intelligence in Advertising: Advancements, Challenges, and Ethical Considerations in Targeting, Personalization, Content Creation, and Ad Optimization. SAGE Open, 13 (4). https://doi.org/10.1177/21582440231210759
21. Patel, N., Trivedi, S., Faruqui, N. (2023). A Novel Sedentary Workforce Scheduling Optimization Algorithm using 2nd Order Polynomial Kernel. 2023 International Conference on Smart Computing and Application (ICSCA). https://doi.org/10.1109/icsca57840.2023.10087492
22. Faruqui, N., Yousuf, M. A., Chakraborty, P., Hossain, Md. S. (2020). Innovative Automation Algorithm in Micro-multinational Data-Entry Industry. Cyber Security and Computer Science, 680–692. https://doi.org/10.1007/978-3-030-52856-0_54
23. Kosinski, M., Stillwell, D., Graepel, T. (2013). Private traits and attributes are predictable from digital records of human behavior. Proceedings of the National Academy of Sciences, 110 (15), 5802–5805. https://doi.org/10.1073/pnas.1218772110
24. Costa, P. T., McCrae, R. R. (1999). A five-factor theory of personality. The five-factor model of personality: Theoretical perspectives, 2, 51–87. Available at: https://www.researchgate.net/publication/284978581_A_five-factor_theory_of_personality
25. Roccas, S., Sagiv, L., Schwartz, S. H., Knafo, A. (2002). The Big Five Personality Factors and Personal Values. Personality and Social Psychology Bulletin, 28 (6), 789–801. https://doi.org/10.1177/0146167202289008
26. Diener, E., Lucas, R. E. Personality traits. General psychology: Required reading. Available at: https://nobaproject.com/textbooks/lauren-brewer-new-textbook/modules/personality-traits
27. Grochowska, A., Młyniec, A., Hryniewicz, K., J zefowicz, E., Ponikowska-Szmajda, K., Kaczmarek (Ozimek), A. et al. (2024). How does personality affect perception of advertising messages? The Big Five model and advertising responses: a meta-analysis. International Journal of Advertising, 1–23. https://doi.org/10.1080/02650487.2024.2321806
28. Hossain, M. E., Faruqui, N., Mahmud, I., Jan, T., Whaiduzzaman, M., Barros, A. (2023). DPMS: Data-Driven Promotional Management System of Universities Using Deep Learning on Social Media. Applied Sciences, 13 (22), 12300. https://doi.org/10.3390/app132212300
29. Achar, S., Faruqui, N., Bodepudi, A., Reddy, M. (2023). Confimizer: A Novel Algorithm to Optimize Cloud Resource by Confidentiality-Cost Trade-Off Using BiLSTM Network. IEEE Access, 11, 89205–89217. https://doi.org/10.1109/access.2023.3305506
30. Moorefield-Lang, H. M. (2015). User agreements and makerspaces: a content analysis. New Library World, 116 (7/8), 358–368. https://doi.org/10.1108/nlw-12-2014-0144