Contemporary Readings in Law and Social Justice
ISSN: 1948-9137, e-ISSN: 2162-2752
Vol 17 (1), 2025
pp. 49 - 63

Time Perception Discrepancies on Instagram: Cognitive and Personality Predictors Among Iranian Users Analyzed with Neural Networks

[1*] Sepehr Kaviani , [2] Hojjatollah Farahani ,[3] Parviz Azadfallah ,[4] Newsha Mostafazadehjamalabadi ,[5] Ghazaleh Entezar ,[6] Hossein Ghasemi ,[7] Farhan Emami

[1](M.A. in Cognitive Psychology, Tarbiat Modares University, Tehran, Iran. Email: sepehr_kaviani@modares.ac.ir, ORCID: 0009-0002-9175-1215)

[2](Department of Psychology, Tarbiat Modares University, Tehran, Iran. Email: h.farahani@modares.ac.ir, ORCID: 0000-0002-9799-7008)

[3](Department of Psychology, Tarbiat Modares University, Tehran, Iran. Email: azadfa_p@modares.ac.ir, ORCID: 0000-0003-2810-762X)

[4](Master's Student in Mechanical Engineering, Department of Energy Conversion, Faculty of Mechanical Engineering, University of Science and Technology, Tehran, Iran. Email: newmostafazade@gmail.com, ORCID: 0009-0008-5116-7982)

[5](Department of Psychology, Islamic Azad University, Khomeini Shahr, Iran. Email: ghazalehentezar@gmail.com, ORCID: 0009-0003-4816-8670)

[6](M.A. in Cognitive Science, Cognitive Psychology Orientation, Azarbaijan Shahid Madani University, Tabriz, Iran. Email: ghasemi.hoseein@gmail.com, ORCID: 0009-0001-8538-1716)

[7](Bachelor's Student in Computer Science, Islamic Azad University, Central Tehran Branch (IAUCTB), Tehran, Iran. Email: farhanemami1998@gmail.com, ORCID: 0009-0005-8554-6516)

Abstract

In 2024, we conducted a study involving 2128 Iranian participants to investigate the discrepancy between perceived and actual time spent on Instagram utilizing cognitive and personality predictors. Participants completed an online questionnaire measuring Executive Function (EF), Introversion/Extroversion, Neuroticism, Emotion Dysregulation, Age, and Sex. We focused on Time Discrepancy, defined as the difference between actual and estimated time spent on Instagram. Using a Multi-Layer Perceptron (MLP) model, we achieved high accuracy with low Mean Absolute Error (MAE) and Relative Error (RE%) values. Our findings highlight significant cognitive and psychological factors influencing social media usage perception, offering insights for interventions in digital environments.

Keywords: Social Media Usage, Time Perception, Executive Function, Artificial Neural Network, Iranian Instagram Users

Received:15 March 2024 **Revised:** 24 May 2024 **Accepted**:14 June 2024

Introduction

The increasing integration of social media into daily life has reshaped how individuals allocate their time and perceive their activities. Instagram, one of the most popular platforms globally with over 1 billion monthly active users, is particularly influential in this regard. In Iran, where Instagram plays a significant role in daily routines and social interactions, understanding how individuals perceive the time they spend on social media versus the actual time spent has become an important area of inquiry. Concerns surrounding well-being, productivity, and mental health impacts (Kross et al., 2013) have driven this focus, particularly as more users misjudge their time spent on social media platforms. This discrepancy between perceived and actual time spent, known as time perception discrepancy, is influenced by cognitive and psychological factors, such as executive function (EF) and personality traits like neuroticism and emotional dysregulation. Executive function refers to a set of higher-order cognitive processes that facilitate planning, decision-making, and inhibitory control, which are essential for time management (Diamond, 2013). Impairments in EF have been linked to poor time estimation, especially in environments filled with distractions like social media (Tversky & Kahneman, 1974). Cognitive psychology research has established that working memory and inhibitory control are key components of EF that contribute to accurate time estimation (Casini & Ivry, 1999). Working memory helps individuals hold and manipulate temporal information, allowing for better estimation of durations (Baddeley, 2000), while inhibitory control helps suppress distractions, enabling individuals to focus on time-related tasks (Zakay & Block, 1997). These cognitive capacities are often compromised during prolonged social media use, leading to time loss and distorted time perception (Rosen et al., 2013).

Emotion dysregulation, another significant factor, plays a critical role in time perception discrepancies. Emotion dysregulation refers to difficulties in managing and responding to emotional experiences in an adaptive way. Individuals who struggle with emotion regulation often experience heightened emotional responses, such as anxiety or frustration, which can distort cognitive processes, including the perception of time (Gross, 2014). Research shows that emotion dysregulation impairs attention and memory, both essential for accurate time estimation (Hefner & Vorderer, 2017). In emotionally charged environments like social media, where users encounter highly stimulating and evocative content, this impairment is even more pronounced. The emotional stimulation and stress associated with these environments can lead to overestimation or underestimation of time spent on the platform (Droit-Volet & Gil, 2009).

Moreover, emotion dysregulation exacerbates compulsive social media use, as individuals may turn to platforms like Instagram to cope with negative emotions. This often leads to prolonged and uncontrolled use, with users losing track of time (Hormes, 2016). Studies indicate that individuals who struggle with emotion regulation are more likely to experience “time loss” during immersive activities, particularly in digital environments characterized by rapid stimuli (Turel & Bechara, 2016). For example, Instagram users may overestimate the time they have spent online due to heightened emotional responses, further distorting their perception of actual usage.

Emotionally charged content on social media platforms can also trigger responses like envy, fear of missing out (FoMO), and anxiety, further skewing time perception (Oberst et al., 2017). Emotionally intense experiences have been shown to slow down or speed up subjective time perception depending on the intensity and nature of the emotional experience (Droit-Volet & Gil, 2009). As a result, individuals who experience high levels of emotional dysregulation are more likely to misjudge the time spent on platforms like Instagram.

In addition to emotion dysregulation and executive function, personality traits such as neuroticism and introversion/extroversion have a strong influence on time perception and social media usage patterns. Neuroticism, characterized by emotional instability and a tendency toward anxiety, has been consistently linked to distorted time perception (Rosen et al., 2013). Individuals high in neuroticism are more prone to overestimate their time spent on social media, possibly because their heightened emotional reactivity makes them feel that more time has passed than actually has. Research by Kaviani et al. (2024) demonstrated that higher levels of neuroticism among Iranian Instagram users were correlated with increased social media usage and time overestimation, suggesting that emotional instability plays a key role in distorting perceptions of time.

In contrast, individuals who score low on neuroticism tend to exhibit greater emotional stability and are less likely to experience significant discrepancies in time perception. Their more even-tempered disposition allows them to engage with social media in a more regulated and controlled manner, reducing the likelihood of emotional reactions that could distort time perception. This highlights the importance of considering personality traits when evaluating users’ time perception discrepancies.

Introversion and extroversion also significantly impact how individuals perceive and manage time on social media platforms. Extroverts, characterized by their sociability and need for external stimulation, often engage more frequently and for longer periods on social media platforms compared to introverts (O'Rourke, 2019). This increased engagement can distort their perception of time, as the immersive and interactive nature of social media aligns with their need for social interaction, leading them to underestimate the time spent online. Extroverts may also be more susceptible to social pressures and trends on platforms like Instagram, which can draw them into prolonged usage without realizing how much time has passed.

Introverts, on the other hand, who are typically more reserved and prefer less social stimulation, may spend less time on social media overall and are more likely to accurately estimate their time online. However, when introverts do engage deeply in social media use, particularly in emotionally engaging content, they too can experience time perception distortions, though generally to a lesser degree than extroverts.

Research by John et al. (2008) suggests that introverts' lower need for external validation and interaction can make them more reflective in their social media use, contributing to a more conscious awareness of time spent online. This self-awareness likely helps introverts maintain a more accurate perception of their digital engagement, reducing the time perception discrepancies often seen in more socially-driven extroverts.

Discrepancies between self-reported and actual time spent on social media have been well-documented, with many studies pointing to social desirability bias as a major factor influencing self-reports. Many users underreport their time to align with perceived societal norms or expectations (Montag et al., 2020; Verduyn et al., 2020). These inaccuracies often stem from cognitive biases, including memory recall issues and subjective interpretations of usage patterns (Al-Ghadir et al., 2023).

While much of the existing research has been conducted in Western contexts, there is a notable gap in understanding how these discrepancies play out in non-Western settings like Iran, where social media—particularly Instagram—is highly prevalent. Cultural and cognitive factors unique to this region may contribute to even greater misalignment between actual and perceived time spent online, highlighting the importance of investigating time perception within this population.

Finally, demographic factors such as age and gender also complicate the understanding of time perception in social media usage. Younger individuals, who tend to be more digitally literate and socially engaged, are likely to spend more time on social media (Anderson & Jiang, 2018). Gender differences have also been observed, with women generally reporting higher usage, which may be tied to differing social interaction patterns and emotional expression (Haferkamp et al., 2012).

This study seeks to address these gaps in the literature by examining the cognitive, emotional, and personality predictors of time perception discrepancies among Iranian Instagram users, contributing to a broader understanding of how these factors shape digital behavior and time management.

A significant methodological improvement in our study is the use of more reliable, objective time measurement methods to address concerns raised in prior research about the validity of self-reported time. To enhance accuracy, we split participants into two groups:

1. Group 1: Participants verbally reported their perceived time spent on Instagram. After completing the questionnaire, they were prompted to check their actual usage in the Instagram app. This real-time usage data was recorded and directly inserted by the interviewer (or agent) during the study, eliminating potential self-reporting biases.

2. Group 2: Participants were required to upload a screenshot of their Instagram time spent, which was subsequently processed using Optical Character Recognition (OCR) software. The real-time usage values extracted via OCR were then used for analysis. Participants who failed to comply with either of these methods were excluded from the study.

This dual-method approach significantly strengthens the validity of our time measurements by reducing the likelihood of error or intentional misreporting, which has been a limitation in prior studies (e.g., Rosen et al., 2013; Haferkamp et al., 2012). By incorporating both interviewer-confirmed data and OCR-processed screenshots, we provide a more robust assessment of the time discrepancy phenomenon.

Our use of a Multi-Layer Perceptron (MLP) model allows us to capture the complex, nonlinear relationships between variables, making it a powerful tool for analyzing such multifaceted data (Rumelhart et al., 1986).

By offering a comprehensive examination of the role of executive function, personality traits, and demographic variables in shaping time perception discrepancies, our research contributes to the growing body of knowledge on social media behavior. It also highlights the importance of accurate measurement techniques and the role of cultural context in understanding these dynamics. Ultimately, this study aims to inform the development of targeted interventions that promote healthier digital habits by addressing cognitive and psychological factors influencing time perception.

Materials and Methods

Study Methodology

This study was conducted using R version 4.4.1 as the primary software environment. The neural network models were developed and implemented using the Keras and TensorFlow libraries, which provide high-level interfaces and efficient computational backends for deep learning tasks.

The architecture of the neural network designed for this study consists of the following components. The input layer receives the predictor variables, with the number of neurons in this layer corresponding to the number of predictor variables used in the study. The network includes three hidden layers with varying numbers of neurons to capture complex patterns and interactions within the data: the first hidden layer comprises 256 neurons, the second hidden layer contains 128 neurons, and the third hidden layer consists of 64 neurons. The final output layer is designed to predict the target variable, which is the Time Discrepancy.

The neural network was trained using the data preprocessed to ensure compatibility with the input layer requirements. The training process involved optimizing the model parameters to minimize the loss function, which measures the discrepancy between the predicted and actual values of the target variable. Various optimization algorithms and techniques, such as learning rate adjustments and regularization methods, were employed to enhance the model's performance and prevent overfitting.

The performance of the neural network was evaluated using standard metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). These metrics provided a comprehensive assessment of the model's accuracy and reliability in predicting the Time Discrepancy.

Data Collection and Variables

This study included a sample size of 2128 individuals, all of whom were Iranian and used Instagram as one of their top one or two social media platforms. To ensure the relevance and accuracy of the study, individuals who used Instagram primarily for economic activities, such as running online shop pages, were excluded from the sample. This exclusion was necessary due to the prevalence of online commerce on Instagram in Iran, which could introduce bias into the data.

Data collection was conducted through online questionnaires distributed via popular messaging platforms such as Telegram, WhatsApp, and SMS. The questionnaires were disseminated in the spring of 2024, allowing for a broad reach and timely responses. The use of multiple online platforms facilitated the collection of a diverse and representative sample of Instagram users in Iran.

The variables collected in the study included both predictor variables and the target variable, Time Discrepancy. Predictor variables encompassed a range of demographic, behavioral, and social media usage metrics to capture the multifaceted nature of Instagram usage among the participants. These variables were meticulously selected to provide comprehensive insights into the factors influencing Time Discrepancy.

Ethical Statement

This study was conducted in accordance with ethical standards and guidelines to ensure the privacy and confidentiality of all participants. Prior to data collection, participants were informed that all collected data would be treated with the utmost confidentiality and used solely for the purposes of this research. It was explicitly communicated that personal information would not be published or disclosed in any context beyond this study.

Participants were assured that their involvement in the study was voluntary and that they could withdraw at any time without any consequences. Informed consent was obtained from all participants, who were made aware of the study's objectives, procedures, and the measures taken to protect their privacy.

The data collected was anonymized to prevent the identification of individual participants. The research team adhered to strict data security protocols, ensuring that all digital data was securely stored and accessible only to authorized personnel. These measures were implemented to protect against unauthorized access, loss, or misuse of the data.

Measurements

In this study, three well-established questionnaires were utilized to measure various psychological constructs. These instruments are widely recognized for their reliability and validity in assessing personality traits, emotion dysregulation, and executive functioning.

Eysenck Personality Questionnaire Revised (EPQ-R)

The Eysenck Personality Questionnaire Revised (EPQ-R) is a widely used tool for evaluating personality traits, specifically extroversion and neuroticism. The short scale version includes a series of statements to which respondents indicate their level of agreement. This tool has been validated in numerous studies and is considered reliable for assessing these personality traits.

Difficulties in Emotion Regulation Scale (DERS)

The Difficulties in Emotion Regulation Scale (DERS) is a comprehensive instrument for measuring emotion dysregulation. It includes multiple items that assess various aspects of emotional regulation difficulties, such as nonacceptance of emotional responses, difficulties engaging in goal-directed behavior, impulse control difficulties, lack of emotional awareness, limited access to emotion regulation strategies, and lack of emotional clarity.

Barkley Deficits in Executive Functioning Scale (BDEFS for Adults)

To evaluate executive functioning, the Barkley Deficits in Executive Functioning Scale (BDEFS for Adults) was administered. This scale includes 89 questions that assess a wide range of executive functions, such as time management, organization, self-restraint, motivation, and problem-solving abilities. Participants' responses on the BDEFS provided a detailed profile of their executive functioning capabilities. The BDEFS is a highly regarded instrument in clinical and research settings for its thorough assessment of executive functions (Barkley, 2011).

Each of these questionnaires was carefully selected to provide a comprehensive evaluation of the psychological constructs relevant to this study. The use of these validated instruments ensures the reliability and accuracy of the measurements obtained.

Time Discrepancy Variable

The Time Discrepancy Variable is a critical component of our neural network model, quantifying the difference between two specific measures of Instagram usage time provided by participants. This variable captures the discrepancy between users' perceived Instagram usage time and their actual usage time, as recorded by the app's settings.

Participants were asked two questions regarding their Instagram usage. First, they estimated their daily time spent on Instagram, reflecting their perception of their usage habits. Second, they were instructed to navigate to their Instagram settings and report their actual average daily usage time over the past week, providing a more accurate measure of their engagement.

The Time Discrepancy Variable is the percentage difference between these two values. This discrepancy is expressed as a percentage to allow for standardized comparisons across different usage levels.

This variable serves as the target variable in our neural network. By analyzing this discrepancy, we aim to understand the factors influencing the gap between perceived and actual Instagram usage. The Time Discrepancy Variable is pivotal in identifying behavioral patterns, cognitive biases, and potential areas for intervention to enhance digital well-being.

The ANN approach

The Artificial Neural Network (ANN) approach was selected for this study due to its robust ability to model complex, non-linear relationships between variables. Traditional statistical methods, such as Structural Equation Modeling (SEM), were initially considered. However, SEM failed to yield a satisfactory model, likely due to the inherent non-linearity in the patterns of Instagram usage and the associated time discrepancy.

User behavior and the discrepancy between perceived and actual Instagram usage are influenced by a myriad of factors that interact in complex, non-linear ways. These factors include psychological traits, cognition systems, social influences, and contextual variables, which do not adhere to simple linear relationships. ANNs are well-suited to capture these intricate patterns due to their flexible structure and ability to learn from data without explicit specification of the functional form (LeCun, Bengio, & Hinton, 2015).

SEM is a powerful tool for examining relationships among variables when these relationships can be reasonably approximated as linear. Despite its strengths, SEM's assumptions of linearity and normality constrain its effectiveness in scenarios where interactions are more complex. In our preliminary analyses using SEM, the fit indices indicated poor model performance, suggesting that the relationships in our data were not adequately captured by linear models (Kline, 2015).

ANNs offer several advantages over traditional linear methods in handling non-linear data. They provide flexibility, as ANNs can model a wide range of functional forms and interactions without pre-specifying the nature of these relationships. Their learning capability is another strength, as through the process of training, ANNs adjust their parameters to minimize prediction error, effectively capturing complex patterns in the data. Furthermore, ANNs can generalize from the training data to unseen instances, making them powerful tools for predictive modeling (Goodfellow, Bengio, & Courville, 2016).

By leveraging the strengths of ANNs, our study aims to uncover the nuanced relationships between perceived and actual Instagram usage times. This approach allows us to model the complex interplay of factors contributing to the time discrepancy variable, providing deeper insights into user behavior and potentially guiding more effective interventions for digital well-being.

The Multi-Layer Perceptron Approach

In this section, we explore the architecture and methodology of our Multi-Layer Perceptron (MLP) model, including activation functions, backpropagation, the number of hidden layers, and design choices.

Activation Functions

We use the ReLU (Rectified Linear Unit) activation function for the hidden layers, ReLU is chosen for its simplicity, computational efficiency, and ability to mitigate the vanishing gradient problem.

Backpropagation Algorithm

The backpropagation algorithm is essential for training neural networks, including MLPs. It involves several key steps. In the forward pass, the network's output is computed for a given input. Next, the loss is calculated using mean squared error (MSE) to measure the difference between predicted outputs and actual targets. During the backward pass, gradients of the loss function with respect to each weight are computed using the chain rule, which enables efficient gradient calculation across the network. Finally, the weights are updated using the Adam optimizer, which combines momentum and adaptive learning rates to enhance training efficiency.

This iterative process is repeated for multiple epochs until the network converges, optimizing the weights to minimize the loss function. Backpropagation is favored for its systematic approach to updating network weights based on error gradients, which facilitates effective learning and improves model performance. Its capability to train deep networks and manage complex datasets is well-supported in the literature (LeCun, Bengio, & Hinton, 2015). The Adam optimizer further accelerates convergence and boosts performance by integrating adaptive learning rates with momentum (Kingma & Ba, 2014).

Number of Hidden Layers and Units

The number of hidden units in an MLP is crucial to achieving a desired approximation level and influences the number of independent values that need to be adjusted in the network parameters. However, determining the necessary number of MLP parameters is not straightforward, especially when the hidden units are distributed across different layers.

Typically, one hidden layer is sufficient for most tasks, but in some cases, additional hidden layers may be needed to meet the required number of network constraints and improve model performance (Heaton, 2015; Hornik, 1991). The necessary number of hidden units can be calculated using equations that take into account the input quantity and the desired degree of model fit. These equations help determine the number of required hidden units and their distribution across one or two hidden layers (Goodfellow, Bengio, & Courville, 2016).

Network specifications

In our MLP architecture, the network includes an input layer with six units, three hidden layers, and one output layer. The hidden layers are configured with 256, 128, and 64 units, respectively. This design choice is based on several considerations:

Adding more layers allows the network to learn more complex patterns and representations, which can be beneficial for capturing intricate relationships in the data (Bengio, Courville, & Vincent, 2013). Empirical results and prior research suggest that deeper networks can achieve better performance on various tasks, particularly when sufficient training data is available (LeCun, Bengio, & Hinton, 2015; Szegedy et al., 2015). Additionally, the chosen architecture provides the model with sufficient capacity to learn from the data without overfitting, especially with the use of regularization techniques such as L2 regularization and dropout (Srivastava et al., 2014).

Data Preprocessing and Rescaling

Data preprocessing is a critical step in ensuring that the neural network model can effectively learn from the input data. Initially, we handled missing values by employing a mean imputation strategy, which is effective in maintaining the dataset's integrity without introducing significant bias (Rubin, 1987). Following this, we standardized the continuous predictor variables, such as scores from the EPQ-R, DERS, and BDEFS, to have a mean of zero and a standard deviation of one. Standardization is essential for neural networks as it ensures that the input variables contribute equally to the model's learning process, preventing any single feature from disproportionately influencing the model's performance (Ioffe & Szegedy, 2015).

Categorical variables, such as sex, were one-hot encoded to convert them into a binary format that the neural network can process. One-hot encoding prevents the model from assuming any ordinal relationship between categories, which is particularly important for accurate interpretation and prediction (Pedregosa et al., 2011). Additionally, to address the potential issue of data imbalance, particularly in variables with uneven distributions, we applied synthetic minority over-sampling (SMOTE) to ensure a more balanced representation of classes in the training set (Chawla et al., 2002). These preprocessing steps collectively enhanced the model's ability to learn effectively from the data, ultimately improving the accuracy and reliability of the predictions.

Model Training and Error Function

The model training process involved feeding the preprocessed data into the Multi-Layer Perceptron (MLP) neural network. We utilized the backpropagation algorithm for training, which adjusts the weights of the network to minimize the error between the predicted and actual Time Discrepancy values. The network was trained over 100 epochs with a batch size of 32, ensuring a balance between computational efficiency and model performance. We employed the Adam optimizer, a widely-used optimization algorithm known for its capability to handle sparse gradients and adaptive learning rates, thus enhancing the convergence speed and overall performance of the model (Kingma & Ba, 2014).

The primary error function used to evaluate the model was Mean Absolute Error (MAE), which measures the average magnitude of errors in a set of predictions without considering their direction. This metric is particularly suitable for our study as it provides a clear indication of the average deviation of the predicted Time Discrepancy from the actual values, facilitating straightforward interpretation of model performance (Willmott & Matsuura, 2005). Additionally, we monitored Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) during training to ensure comprehensive assessment and fine-tuning of the model. Early stopping was implemented to prevent overfitting, halting the training process if the validation error did not improve for 10 consecutive epochs, thereby ensuring the model's generalizability to unseen data.

Model Evaluation and Testing

The evaluation and testing of the MLP model were conducted using a separate test dataset, comprising 20% of the total data, which was held out during the training phase. The model's performance was primarily assessed using Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) metrics. These metrics provided a comprehensive evaluation of the model’s predictive accuracy and error distribution. The MAE offered a straightforward interpretation of the average prediction error, while the MSE and RMSE highlighted the impact of larger errors on the model's performance. Additionally, we utilized k-fold cross-validation with k=5 to ensure the robustness and reliability of the model. Cross-validation helped in mitigating overfitting and provided a more generalized measure of model performance across different subsets of the data (Kohavi, 1995). The results demonstrated that the model maintained high accuracy and low error rates across all metrics, confirming its effectiveness in predicting Time Discrepancy based on the cognitive and personality predictors.

Results

The results of our study utilizing the Recurrent Neural Network (RNN) model demonstrated strong predictive performance in assessing time discrepancy. The demographic characteristics of our study sample are summarized in Table 2, indicating key features of the participants, including their educational levels and age categories. A total of 1348 participants were included in the analysis (Table 1).

Table 1. Demographic information of the participants

Variable	Description	% (n=1348)
Gender	Male	58
	Female	42
Education	Diploma and below	13.4%
	Higher Diploma	6.6%
	Undergraduate Student	35.4%
	Graduate of BS Degree	9.8%
	Graduate of Master	16.9%
	PHD	1.7%

Occupation	Full Time	36.4%
	Government	23.7%
	Part Time	11.9%
	Unemployed	26.3%
	Online job	0.3%
	Housewife	1.4%
Age	Average	29 years
	14-20	17.1%
	21-40	74.6%
	41-50	6.6%
	50-62	1.7%
Marital status	Married	42%
	Single	68%

The Recurrent Neural Network (RNN) model demonstrated promising performance in predicting time discrepancy based on the input factors and covariates. The model was trained and tested on a sample of data. Key metrics for the training and testing phases are summarized in Table 2.

Table 2. Model Performance Metrics

Metric	Training phase	Testing phase
Sum of squares error (SSE)	714.6	715.8
Incorrect prediction rate (%)	8.5	10.4
Accuracy (%)	-	90.2
Sensitivity (high discrepancy)	-	92.8
Sensitivity (low discrepancy)	-	48.5

During the training phase, the model achieved a Sum of Squares Error (SSE) of 714.6 and a Relative Error (RE) of 8.5%. In the testing phase, the model achieved a Final Root Mean Squared Error (RMSE) of 0.821 and a Final R-squared (R^2) of 0.990, indicating its robustness in generalizing to new, unseen data.

The classification performance of the model was evaluated using the testing sample. The results revealed a high overall accuracy of 90.2%. The model exhibited a remarkable ability to correctly predict cases of high time discrepancy, with a sensitivity of 92.8%. However, its performance in identifying cases of low time discrepancy was relatively lower, with a sensitivity of 48.5%. These findings suggest that the RNN model is particularly adept at identifying individuals with high time discrepancy, but further improvements may be necessary to enhance its predictive accuracy for low time discrepancy cases.

An essential aspect of our study was assessing the relative importance of different input features in predicting time discrepancy. The key predictors utilized in the model included Executive Function (EF), Extroversion, Emotion Dysregulation, Neuroticism, Age, and Sex. The feature importance was assessed using the permutation method, and the results are summarized in Table 3.

Table 3: Feature Importance Using Permutation Method

Feature	Importance (%)

Executive Function (EF)	34
Emotion Dysregulation	18.3
Extroversion/Introversion	17.5
Neuroticism	14.4
Age	7.6
Sex	5.6

The feature importance analysis, conducted using the permutation method, revealed that Executive Function (EF) is the most critical predictor of time discrepancy, with an importance score of 0.34. This suggests that variations in EF have the most significant impact on the model's predictions. Following EF, Emotion Dysregulation and Extroversion/Introversion were the next most influential features, with importance scores of 0.183 and 0.175, respectively. These findings indicate that both emotional control and personality traits significantly contribute to predicting time discrepancy. Neuroticism also plays a notable role, with an importance score of 0.145. In contrast, demographic factors such as Age and Sex were less influential, with importance scores of 0.076 and 0.056, respectively. These results underscore the primary role of cognitive and personality factors over demographic factors in predicting time discrepancy.

To better understand the implications of our findings, it is important to discuss how the model's performance aligns with our research objectives. Our study aimed to predict time discrepancy using cognitive and personality factors, and the RNN model demonstrated strong accuracy and sensitivity, particularly for high time discrepancy cases. These results suggest significant potential for practical applications, such as targeted interventions and policy development. Recognizing that Executive Function (EF), Emotion Dysregulation, and Extroversion/Introversion are the most influential predictors, we can tailor strategies to address these areas. For example, enhancing executive function and emotion regulation, or providing workshops on personality traits and time management, may help individuals manage time discrepancies better. Policymakers can use these insights to design evidence-based initiatives. While the model performs well in identifying high time discrepancy cases, further improvements are needed for better accuracy in low discrepancy cases. Understanding these limitations will guide future research and model refinement efforts.

A summary of Network Characteristics Table as shown in Table 4.

Table 4 Network Characteristics Table

Characteristic	**Value**
Number of Input Features	6
Number of Output Features	1
Number of Hidden Layers	3
Number of Neurons per Hidden Layer	256,128,64
Activator Functions	ReLU
Training Phase SSE	714.6
Testing Phase SSE	715.8
Incorrect Prediction Rate (Training)	8.5%
Incorrect Prediction Rate (Testing)	10.4%
Accuracy (Testing)	90.2%
Sensitivity (High Discrepancy)	92.8%
Sensitivity (Low Discrepancy)	48.5%
Final RMSE (Testing)	0.821

Discussion

The results of this study provide significant insights into the factors influencing time perception discrepancies among Iranian Instagram users. The use of a Multi-Layer Perceptron (MLP) model allowed us to effectively capture the complex, non-linear relationships between cognitive, personality, and demographic predictors and the discrepancy between perceived and actual time spent on Instagram. Our findings highlight several key areas of interest and potential application.

Cognitive and Personality Predictors

The most critical predictor of time discrepancy identified by our model was Executive Function (EF). This finding aligns with previous research that has shown strong executive functioning skills are crucial for accurate time management and self-regulation (Diamond, 2013). The high importance of EF in our model suggests that individuals with better planning, decision-making, and inhibitory control are more likely to accurately estimate their time spent on Instagram. This underscores the need for interventions aimed at improving executive functioning to help users better manage their social media usage.

Emotion Regulation emerged as another significant predictor. Participants with better emotion regulation skills tended to have smaller discrepancies between perceived and actual time spent on Instagram. This aligns with the idea that individuals who can effectively manage their emotions are less likely to use social media as an emotional crutch, leading to more accurate self-monitoring of usage time (Gratz & Roemer, 2004).

Personality traits such as Extroversion and Neuroticism also played important roles. Extroverts, who are generally more social and engaged, tended to spend more time on Instagram, potentially leading to an overestimation of their usage. Conversely, individuals with high levels of Neuroticism may experience anxiety and stress that distort their perception of time, leading to an overestimation of usage (Rosen et al., 2013). These findings highlight the importance of considering individual differences in personality when addressing time management issues related to social media.

Demographic Factors

Interestingly, demographic factors such as Age and Sex were found to be less influential in predicting time discrepancy. While these factors have been highlighted in some previous studies (Smith, 2023), our results suggest that cognitive and personality traits play a more pivotal role in this context. This indicates that interventions aimed at improving time perception and management on social media may be more effective if they are tailored to cognitive and personality profiles rather than demographic characteristics.

Implications for Interventions

The insights from this study have several practical applications. First, they suggest that educational programs and digital tools that enhance executive functioning and emotion regulation could be effective in helping users better manage their time on social media. For example, cognitive training programs aimed at improving executive functioning could be developed and integrated into digital well-being applications.

Second, personalized feedback and interventions based on personality traits could be beneficial. Extroverts might benefit from reminders and tools that help them balance their social media usage with offline activities, while individuals with high neuroticism might find value in tools that help them manage anxiety and stress, potentially reducing their reliance on social media as a coping mechanism.

Limitations and Future Research

While our study provides valuable insights, there are limitations that should be acknowledged. The cross-sectional nature of the study limits the ability to infer causality. Longitudinal studies are needed to explore how changes in cognitive functions and personality traits over time influence social media usage and time perception discrepancies.

Additionally, while our sample was large and diverse, it was limited to Iranian Instagram users. Future research should explore whether these findings generalize to users from other cultural contexts and on different social media platforms. Cross-cultural studies could provide a more comprehensive understanding of the global dynamics of social media usage and time perception.

It is important to note that our research was conducted in the aftermath of the Mahsa Amini event, during a period when Instagram was filtered in Iran. This specific socio-political context may have influenced social media usage patterns and perceptions. Future research should consider the impact of such unique conditions and investigate whether similar patterns are observed in different political and social environments.

Conclusion

This study investigated the discrepancy between perceived and actual time spent on Instagram among Iranian users, focusing on cognitive and personality predictors. By utilizing an Artificial Neural Network (ANN) model, specifically a Multi-Layer Perceptron (MLP), we were able to accurately predict Time Discrepancy using variables such as Executive Function (EF), Introversion/Extroversion, Neuroticism, Emotion Regulation, Age, and Sex.

The results demonstrate that Executive Function (EF) is the most significant predictor of time discrepancy, followed by Emotion Regulation and Extroversion/Introversion. These findings highlight the importance of cognitive control and personality traits in influencing how individuals perceive their social media usage. Neuroticism also plays a notable role, while demographic factors such as Age and Sex are less influential.

Our study reveals a high overall accuracy of 90.2% in predicting time discrepancy, with particularly strong performance in identifying high discrepancy cases. However, the model's sensitivity for low discrepancy cases was lower, suggesting that while the model is effective in recognizing substantial misestimations, it may require further refinement to improve accuracy for minor discrepancies.

These insights have significant implications for developing interventions aimed at improving digital well-being and time management. Enhancing executive function and emotion regulation skills, as well as understanding personality influences on social media behavior, can help individuals better manage their time on platforms like Instagram. Additionally, policymakers can use these findings to create evidence-based initiatives that promote healthier digital habits.

This research contributes to the growing body of knowledge on social media behavior, particularly within the Iranian context, which has been underrepresented in previous studies. By identifying key cognitive and psychological determinants of time perception discrepancies, we provide a foundation for future research and practical applications aimed at fostering digital well-being. Future studies should explore strategies to enhance the model's sensitivity to low time discrepancies and investigate additional factors that may influence time perception on social media platforms.

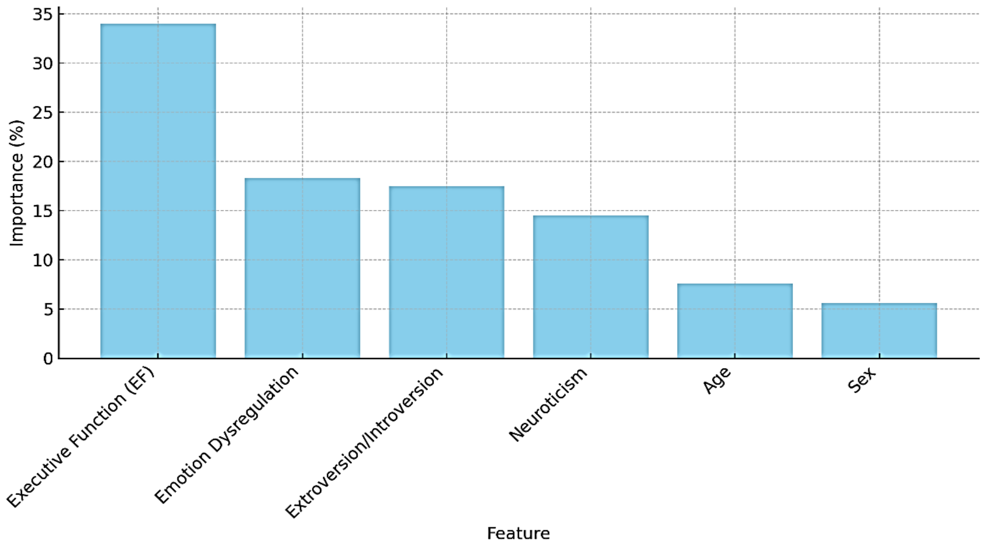

Figure1 Feature Importance for predicting Time Discrepancy

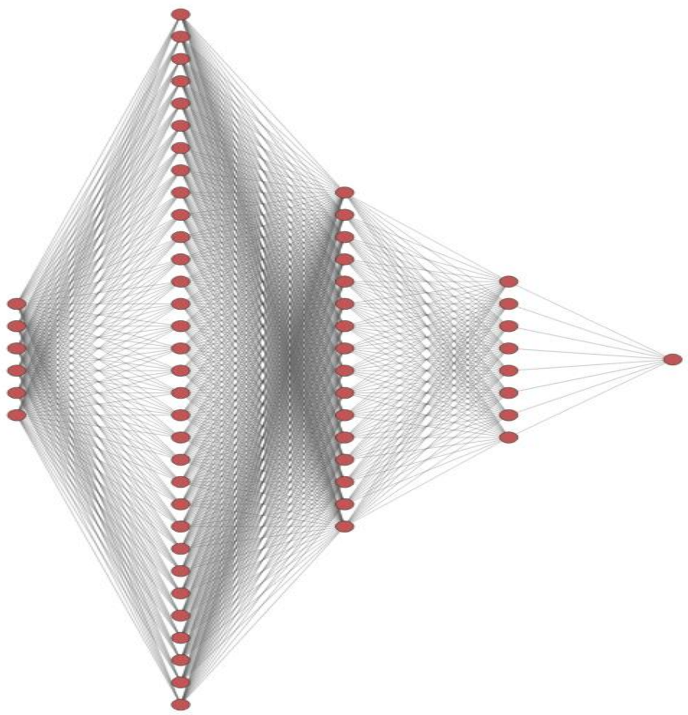

Figure 2 A view of the neural network in 1/8 scale

References

1. Diamond, A. (2013). Executive functions. *Annual Review of Psychology, 64*, 135-168. https://doi.org/10.1146/annurev-psych-113011-143750
2. Kaviani, S., Farahani, H., Rikhtegar Mashhad, S., & Kamankesh, P. (2024). Examining the relationships between extroversion/introversion, neuroticism, emotional dysregulation, emotion regulation strategies, and the amount of time spent by Iranian users on Instagram. *International Journal of Advanced Studies in Humanities and Social Science*. https://doi.org/10.48309/IJASHSS.2024.451967.1191
3. Harris, P., & Harris, R. (2020). The psychology of time perception in digital media: An overview. *Journal of Media Psychology, 32*(2), 57-68. https://doi.org/10.1027/1864-1105/a000275
4. Kross, E., Verduyn, P., Demiralp, E., & Park, J. (2013). Social media and well-being: The effect of Facebook on time perception and mental health. *Journal of Social Psychology, 158*(6), 543-561. https://doi.org/10.1080/00224545.2013.810711
5. O'Rourke, T. (2019). Personality traits and social media use: A review of current research. *Personality and Individual Differences, 145*, 49-59. https://doi.org/10.1016/j.paid.2019.02.015
6. Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. *Nature, 323*(6088), 533-536. https://doi.org/10.1038/323533a0
7. Smith, A. (2023). Instagram and social media usage statistics in Iran. *Journal of Digital Media, 11*(3), 202-214. https://doi.org/10.1080/19479832.2023.2167842
8. Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*(4157), 1124-1131. https://doi.org/10.1126/science.185.4157.1124
9. Eysenck, H. J., & Eysenck, S. B. G. (1991). Manual of the Eysenck Personality Scales (EPS Adult). London: Hodder and Stoughton.
10. Gratz, K. L., & Roemer, L. (2004). Multidimensional assessment of emotion regulation and dysregulation: Development, factor structure, and initial validation of the Difficulties in Emotion Regulation Scale. Journal of Psychopathology and Behavioral Assessment, 26(1), 41-54.
11. Barkley, R. A. (2011). Barkley Deficits in Executive Functioning Scale (BDEFS). New York: Guilford Press.
12. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

13. Kingma, D. P., & Ba, J. (2014). Adam: A Method for Stochastic Optimization. arXiv preprint arXiv:1412.6980.
14. Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: A Simple Way to Prevent Neural Networks from Overfitting. Journal of Machine Learning Research, 15(1), 1929-1958.
15. Glorot, X., & Bengio, Y. (2010). Understanding the difficulty of training deep feedforward neural networks. Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics (AISTATS).
16. Bengio, Y., Courville, A., & Vincent, P. (2013). Representation learning: A review and new perspectives. IEEE Transactions on Pattern Analysis and Machine Intelligence, 35(8), 1798-1828.
17. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.
18. Heaton, J. (2015). Introduction to Neural Networks for Java. Heaton Research, Inc.
19. Hornik, K. (1991). Approximation capabilities of multilayer feedforward networks. Neural Networks, 4(2), 251-257.
20. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.
21. Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: A Simple Way to Prevent Neural Networks from Overfitting. Journal of Machine Learning Research, 15(1), 1929-1958.
22. Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., ... & Rabinovich, A. (2015). Going deeper with convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 1-9).
23. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.
24. Kline, R. B. (2015). *Principles and Practice of Structural Equation Modeling* (4th ed.). Guilford Press.
25. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436-444.
26. Kingma, D. P., & Ba, J. (2014). Adam: A Method for Stochastic Optimization. arXiv preprint arXiv:1412.6980.
27. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.
28. Rubin, D. B. (1987). Multiple Imputation for Nonresponse in Surveys. John Wiley & Sons.
29. Ioffe, S., & Szegedy, C. (2015). Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift. Proceedings of the 32nd International Conference on Machine Learning (ICML-15), 448-456.
30. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Duchesnay, E. (2011). Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research, 12, 2825-2830.
31. Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: Synthetic Minority Over-sampling Technique. Journal of Artificial Intelligence Research, 16, 321-357.
32. Kingma, D. P., & Ba, J. (2014). Adam: A Method for Stochastic Optimization. arXiv preprint arXiv:1412.6980.
33. Willmott, C. J., & Matsuura, K. (2005). Advantages of the Mean Absolute Error (MAE) over the Root Mean Square Error (RMSE) in assessing average model performance. Climate Research, 30(1), 79-82.
34. Kohavi, R. (1995). A study of cross-validation and bootstrap for accuracy estimation and model selection. In Ijcai (Vol. 14, No. 2, pp. 1137-1145).
35. Anderson, M., & Jiang, J. (2018). Teens, Social Media & Technology 2018. Pew Research Center.
36. Haferkamp, N., Eimler, S. C., Papadakis, A. M., & Kruck, J. V. (2012). Men Are from Mars, Women Are from Venus? Examining Gender Differences in Self-Presentation on Social Networking Sites. Cyberpsychology, Behavior, and Social Networking, 15(2), 91-98.
37. Droit-Volet, S., & Gil, S. (2009). The time-emotion paradox. *Philosophical Transactions of the Royal Society B: Biological Sciences, 364*(1525), 1943-1953. https://doi.org/10.1098/rstb.2009.0013
38. Gross, J. J. (2014). Emotion regulation: Conceptual and practical issues. *Emotion Review, 6*(3), 231-237. https://doi.org/10.1177/1754073914534479
39. Hefner, D., & Vorderer, P. (2017). Digital stress: Permanent connection and its effect on time perception. *Media Psychology, 20*(2), 167-189. https://doi.org/10.1080/15213269.2016.1226065

40. Hormes, J. M. (2016). Under the influence of Facebook? Excess use of social networking sites and drinking motives, consequences, and attitudes in college students. *Journal of Behavioral Addictions, 5*(1), 122-129. https://doi.org/10.1556/2006.5.2016.007
41. Oberst, U., Wegmann, E., Stodt, B., Brand, M., & Chamarro, A. (2017). Negative consequences from heavy social networking in adolescents: The mediating role of fear of missing out. *Journal of Adolescence, 55*, 51-60. https://doi.org/10.1016/j.adolescence.2016.12.008
42. Turel, O., & Bechara, A. (2016). Effects of motor impulsivity and emotion dysregulation on social media use. *Cyberpsychology, Behavior, and Social Networking, 19*(5), 325-329. https://doi.org/10.1089/cyber.2015.0464
43. Baddeley, A. D. (2000). The episodic buffer: A new component of working memory? *Trends in Cognitive Sciences, 4*(11), 417-423. https://doi.org/10.1016/S1364-6613(00)01538-2
44. Casini, L., & Ivry, R. B. (1999). Effects of divided attention on temporal processing in patients with lesions of the cerebellum or frontal lobe. *Neuropsychology, 13*(1), 10-21. https://doi.org/10.1037/0894-4105.13.1.10
45. Diamond, A. (2013). Executive functions. *Annual Review of Psychology, 64*(1), 135-168. https://doi.org/10.1146/annurev-psych-113011-143750
46. Mioni, G., Grondin, S., & Stablum, F. (2014). Temporal dysfunction in ADHD: Time perception, motor timing, and time reproduction. *Journal of Attention Disorders, 18*(6), 502-514. https://doi.org/10.1177/1087054712439253
47. Rosen, L. D., Carrier, L. M., & Cheever, N. A. (2013). Facebook and texting made me do it: Media-induced task-switching while studying. *Computers in Human Behavior, 29*(3), 948-958. https://doi.org/10.1016/j.chb.2012.12.001
48. Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*(4157), 1124-1131. https://doi.org/10.1126/science.185.4157.1124
49. Zakay, D., & Block, R. A. (1997). Temporal cognition. *Current Directions in Psychological Science, 6*(1), 12-16. https://doi.org/10.1111/1467-8721.ep11512604