SensorApp: A Digital Mirror Personality Recognition with Deep Learning Using a Mobile Usage Dataset

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***Abstract*— Automatic personality recognition has become relevant due to the advancement of artificial intelligence and the widespread use of mobile devices. This study proposes predicting personality traits according to the OCEAN model by integrating mobile sensor data and self-reports using deep neural networks. Through a mobile application, sensor data and daily surveys related to device usage were collected. Four model architectures (MLP, CNN, LSTM and Transformer) were evaluated, finding that CNN is most effective with raw data, while the Transformer excels at including temporal and frequential attributes. These results represent a breakthrough in customized and empathic technologies in mobile data-based personality recognition. The official implementation code of our method is available at https://github.com/Nestor-Leyva/SensorApp-LatAmTransactions**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/10133

***Keywords*—Personality Recognition, Mobile Sensors, Accelerometer and gyroscope data, CNN, Deep Learning, LSTM, MLP, Transformer.**

I. INTRODUCTION

PERSONALITY is a psychological construct that comprises thought patterns, emotions, and behaviors that characterize and distinguish individuals [1]. Studying personality is fundamental to psychology as it enables understanding and prediction of human behavior in different contexts. Personality recognition focuses on identifying these behavioral patterns through computational tools and methodologies, and has gained relevance in fields such as artificial intelligence, applied psychology, and education.

The increasing use of modern technology, particularly mobile devices, has created new opportunities to study personality as these devices have become an integral part of daily life for a large portion of the global population. Recent data estimates that over half of the world's population owns a cell phone [2]. In countries such as Mexico, 79.2% of the population uses these devices. Moreover, Mexican users spend between 2.7 and 4.7 hours per day on their phones [3]. This extensive usage produces large volumes of data that can be leveraged for behavioral and personality studies.

By integrating data from mobile device sensors, such as accelerometers and gyroscopes, along with self-reported with self-reported questionnaire information, the scope and accuracy of personality recognition can be enhanced [4]. These technologies enable the analysis of movement and behavioral patterns, providing insights into how individuals interact with their devices and their environment. Personality recognition has practical applications including user experience enhancement, behavioral analysis related to mental health, and the development of adaptive and inclusive technologies, such as customer service systems that improve user experience [5]. Additionally, it supports personalized learning and emotional wellness monitoring.

In this study, we use the OCEAN model to examine personality recognition. The model describes personality according to five traits, each one represented by a numerical value that indicates its relative strength. Using mobile device usage data and sensor activity, we modeled personality traits and evaluated state-of-the-art predictive models. Our findings confirm that personality traits can be accurately predicted using mobile sensor data and user-provided information. Among the evaluated neural network architectures, Transformer-based models achieved the best performance, particularly when statistical features from time and frequency domains were incorporated. These results highlight the importance of feature engineering and multimodal data fusion and demonstrate the ability of deep learning approaches to capture complex behavioral patterns associated with personality.

This work provides empirical evidence that personality traits can be inferred from nonintrusive behavioral data collected via mobile sensors, using both traditional and advanced artificial intelligence models. By integrating psychometric assessment with computational modeling, this study contributes methodological advances for exploring individual differences, with potential applications in wellness monitoring, personalized learning, and adaptive technologies.

The remainder of this paper is structured as follows: In Section II a summary of related work is presented. Section III describes the methodology, including data collection and modeling. Section IV reports the experimental results. Finally, Section V presents the conclusions of this work and outlines future work directions.

II. RELATED WORK

This section reviews related work, starting with those related to

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mobile data collection. In this sense, Pires et al. [6] collected a dataset using accelerometer, magnetometer and gyroscope from mobile devices. This was done to analyze five Activities of Daily Living (ADL): walking, running, standing, climbing stairs, and descending stairs. The resultant set consists of approximately 14 hours of recordings with around 10,000 records for each of the sensors. The processed data provided accurate information on movement patterns associated with activity. Authors conclude that this dataset is relevant for developing technological methods to support health, prevent sedentary lifestyles and promote low-cost solutions. Similarly, Li et al. [7] address users' concerns about security measures for accessing banking applications. The authors explore the possibility to develop an application with authentication approach for mobile devices by analyzing the data collected from accelerometer and gyroscope during the first seconds when the application is opened. The Equal Error Rate (EER), commonly used to evaluate the effectiveness of biometric authentication methods, was used to evaluate the performance of their proposed approach, reaching 22.72% using only the data collected from the first 3 seconds after launching the app. From these data they conclude that performance could be improved after incorporating complementary information (such as WiFi and Bluetooth information). Finally, in a similar fashion, the work by Al-Mahadeen et al. [8] explores the use of smartphone accelerometer and gyroscope sensor data to identify and authenticate users. For this, they use deep learning, traditional classifiers and voting algorithms to analyze the HMOG (Hand Movement, Orientation and Grasp) ensemble data. Such methods include Recursive Feature Elimination (RFE) and sliding overlapping windows. Finding that accelerometer data outperforms gyroscope data in authentication, while combining them and using a Long-Short Term Memory (LSTM) network enabled authentication with high accuracy. Demonstrating the effectiveness of deep learning algorithms for user authentication based on motion sensor data.

Regarding automatic personality recognition, Prajapati et al. [9] developed an ensemble of machine learning classifiers to automatically recognize personality from text. Their method analyzes textual data using techniques like Gradient Bagging to predict both Myers-Briggs (MBTI) and Big Five personality types. This is followed by a voting process to determine the levels of the various attributes. Experiments with this model demonstrated that this approach improves the accuracy and stability of predictions, with potential applications across a variety of domains that require personalization and understanding of human behavior. Similarly, Bátiz-Beltrán et al. [10] focus on the creation of a Spanish corpus to detect personality traits automatically using the OCEAN model (called PersonText), which contains 213 Spanish texts generated by participants in the platform called PersonApp. In this platform, users respond the standardized International Personality Item Pool (IPIP) test to create the corpus with the values of the OCEAN traits of each of the test subjects. Different machine and deep learning models were used to evaluate the corpus, such as Multi-Layer Perceptron (MLP), LSTM and Convolutional Neural Networks (CNN). It is concluded that the results show promising advances, since models such as LSTM reached values higher than 70% in accuracy in the 5 personality traits of OCEAN. Finally, Tinwala et al. [11] developed a model based on deep convolutional neural networks (CNN) to detect Big Five personality traits. This method involves using pre-trained word embeddings to create feature representations to use them as input for CNN. The model was reported to predict personality traits with high accuracy by identifying linguistic patterns and correlating them with the OCEAN categories. The authors comment that neural networks offer an effective method to detect personality traits from text, overcoming the limitations of traditional approaches such as questionnaires

In the same way, the area of personality recognition based on mobile devices has some previous work that serves as a basis for the current article. Such is the case of the work by Xenakis et al. [12], that focuses on personality recognition using mobile devices. They developed iOS and Android apps to collect data from smartphone sensors, including accelerometers, gyroscopes, app usage, and activity patterns. Positive correlations were found between some features of the HEXACO personality model and sensor data, finding correlations between smartphone usage patterns and the HEXACO model personality dimensions. Although the authors did not report numerical results, they suggest that such sensor data could be used for accurate personality detection. On the other hand, the work of Ibrar et al. [13] presents a system that uses mobile device sensors to evaluate OCEAN model personality traits by recognizing walking patterns. The data processing involved segmentation, filtering, and time series feature extraction. Classification was then performed with machine learning algorithms such as Support Vector Machines (SVM). Accuracy values above 94% were obtained in the detection of activities like walking. With this, they concluded that walking patterns recognized by smartphone sensors can effectively infer personality traits. Finally, Bhatele et al. [14] developed a system to recognize gestures on mobile device screens using the embedded sensors, specifically the accelerometer and gyroscope. Data was obtained from 47 users performing common gestures (scrolling, zooming, touching the screen, changing orientation, etc.). Subsequently, the model was trained using classifiers such as Random Forest and K-Nearest Neighbors. The best performing was Random Forest with an accuracy of 97%. This is evidence that the data collected from mobile sensors can be effectively used to identify gesture interactions on the screen. More recently, Sze et al. [15] reported that personality can be predicted with high reliability from activity data collected using mobile sensors. They used accelerometer records and movement patterns data in a binary classification experiment to distinguish between two levels of personality traits, achieving an F1 score of up to 0.78. This result highlights the value of sensor-derived characteristics for personality inference and demonstrates the effectiveness of applying classification algorithms to activity data based on sensors. In a similar approach, Kovacevic et al. [16] further demonstrated that their system could predict personality traits at two levels (low and high) by analyzing short-term behavioral data collected from mobile sensors. They conducted experiments using daily measurements and longitudinal tracking over ten weeks. They reported an accuracy of up to 74.5% and an Area Under the Curve (AUC) of 0.72 on a single day data, which improved to an accuracy of 84.5% and an AUC of 0.79 after ten weeks of data collection. All this suggests that even short-term behavioral data can effectively infer personality traits, supporting the usefulness of mobile sensing in longitudinal studies.

In the field of artificial intelligence applications in psychology, complementary directions have been explored in recent years, mainly related to affective computing and behavior analysis using artificial intelligence. For example, Ali et al. [17] proposed a framework to analyze opinions based on aspects of ride-sharing platform reviews to support Kansei engineering, a method aimed at bringing service design in line with user emotions. Their approach combined multilingual text processing, including translations from Romanized Urdu/Hindi and English, with unsupervised machine learning to group customer opinions according to key aspects of the service, such as “Driver,” “Company,” “Service,” and “Ride.” Through a structured process that included tokenization, parts of speech tagging, feature extraction, and polarity classification, the authors identified the most frequent positive and negative expressions, providing useful insights for service improvement. Their results demonstrated that integrating multilingual user comments into Kansei engineering allows for a more accurate reflection of customer satisfaction, especially in South Asian markets. In a different field, Huang [18] developed a system for facial emotion recognition that combines multiple convolutional neural network (CNN) architectures to improve the accuracy of image-based affect detection. Two models, Visual Geometry Group Networks (VGG) and ResNet, were trained on a modified version of the Kaggle Facial Expression Recognition dataset, followed by fusion strategies in both, the earlier and later training phases. The study evaluated several fusion mechanisms, including feature concatenation with linear Support Vector Machines (SVMs) and majority voting, by determining their impact on classification performance. The late fusion approach, in particular, achieved the highest accuracy recorded, at 87.4%, surpassing the results of the individual models. These findings confirm that hybrid deep learning architectures can significantly improve emotion classification accuracy by capturing complementary feature representations across models. More recently, the work by Gao et al. [19] shifted the focus toward continuous estimation of personality traits using deep learning. They proposed a multitask and multivision learning framework to infer Big Five traits from smartphone usage snapshots, addressing the problem as a regression task. The performance of their model was evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), with results ranging from 0.256 to 0.510 for MAE and 0.305 to 0.647 for RMSE across the different traits. Using these metrics, they demonstrated the potential of neural networks to capture complex psychological patterns from digital footprints. Finally, Leibo et al. [20] presented Psychlab, a simulated experimental framework designed to evaluate deep reinforcement learning (RL) agents using psychological paradigms. Based on the DeepMind Lab environment, Psychlab enables controlled testing of agents and humans on tasks such as visual search, motion discrimination, and change detection. The authors conducted a series of psychophysical experiments with the deep RL agent UNREAL, evaluating visual acuity, contrast sensitivity, and object tracking ability. Their findings revealed that UNREAL's learning performance was strongly influenced by target size and contrast, leading to the integration of a model of foveal vision to improve perception. This modification improved the agent's performance on multiple visual tasks, highlighting Psychlab's potential to bridge cognitive science and artificial intelligence by enabling direct comparisons between human and artificial perceptual behavior.

When compared to previous studies, our research stands out by combining data from smartphone sensors with users' self-reported phone usage, resulting in a more comprehensive behavioral dataset compared to other works that rely on only one of these sources. We use personality scores validated according to the OCEAN model (via the IPIP questionnaire) as a reference to train deep learning models that detect patterns, linking mobile behavior to personality traits. Unlike previous approaches, our feature engineering integrates basic statistics from mobile sensor readings and complements them with time and frequency domain attributes. This comprehensive framework enables more unbiased, scalable, and real-time personality prediction, overcoming the limitations of traditional self-report methods.

III. Methodology

In this section we describe the process to achieve an accurate characterization of the users' personality. A methodology was designed to collect data, comprising self-reported and sensor sources using mobile devices. In addition, the treatment of the data collected by means of mobile devices is described. Finally, the selection criteria for neural networks for the purpose of prediction are presented.

A. Tools and Instruments for Data Collection

The characterization of personality traits based on the behavior of mobile device users requires the synchronized collection of multimodal data. To accomplish it, a set of specific tools and instruments were used. The data collection methodology contains a custom-developed mobile application to collect data from high-frequency sensors, specifically the accelerometer and gyroscope as well as data on users’ mobile device usage habits, and the standardized psychological survey instruments to assess users’ personality traits. The following subsections elaborate on the individual software and hardware components, which collaborated to constitute the data collection scheme.

Ocean Personality Traits

The Big-Five personality model, commonly referred to as the OCEAN model, is formed by five core dimensions:

Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. This is one of the most widely recognized and empirically supported frameworks in contemporary psychology for describing and assessing personality traits [21]. These are typically represented as continuous values within a normalized range from 0 to 1, where 0 indicates the complete absence and 1 the full presence of a given trait in an individual. As a result, predicting personality traits using this model is framed as a regression problem, where the goal is to estimate continuous personality scores rather than classify individuals into discrete categories. The OCEAN model has demonstrated strong cross-cultural validity and has been systematically associated with numerous life outcomes, including academic success, interpersonal behavior, and mental health [22]. Its scientific robustness and broad applicability make it a foundational tool in both psychological research and technological applications such as Automatic Personality Recognition (APR).

IPIP-50 as an Instrument to Assess Personality Traits

To implement the OCEAN model in this study, personality traits were measured using the International Personality Item Pool (IPIP), a widely used set of items in the public domain developed to assess personality based on the Big Five framework [21, 23]. Specifically, the IPIP-50 test was selected, which consists of 50 self-report items (10 for each of the five personality traits), rated by users on a 5-point Likert scale ranging from 1 (“very inaccurate”) to 5 (“very accurate”). The total score for each trait is normalized on a scale from 0 to 1, with higher values reflecting a greater presence of that personality dimension. In this research work, the IPIP-50 test was integrated into the web version of SensorApp, the data collection platform developed for the study. Users complete the questionnaire online, providing a standardized and quantifiable personality profile that serves as a reference for subsequent modeling. These values are then correlated with behavioral and sensor data captured through the mobile version of SensorApp, enabling the development and evaluation of machine learning models for personality prediction. The proven validity and accessibility of the IPIP framework make it a reliable basis for training APR systems.

Data Collection from Mobile Sensors

We focus on collecting data from mobile sensors to develop personality recognition models, reducing bias by focusing on interactions with mobile devices. For this purpose, accelerometer and gyroscope sensors were considered, since these sensors are available in all devices. In addition, SensorApp Mobile also records audio where users describe strong emotional experiences. For the purposes of this work, these audios will not be taken into consideration for predictions.

The sensor data was collected using the accelerometer and gyroscope built into the mobile device, using the expo-sensors library included in the Expo Go framework to be managed. Both sensors were set up with a sampling frequency of 1.0 Hz, which is the same as an updating interval of 1000 milliseconds. To optimize sensor sensitivity and reduce the influence of small vibrations or insignificant noise, a threshold of 1.2 acceleration units was applied. Raw sensor data, comprising the X, Y, and Z components, was stored in a temporary array for subsequent processing and analysis.

Application Development Specifications

The data collection application, SensorApp, was developed using the development framework Expo Go, which uses the JavaScript-based React Native framework programming in the programming IDE Visual Studio Code. This development framework was chosen due to its fast test and development cycle, as it allows changes to be instantly reflected on the devices; in addition, it allows for multiplatform development (Android, iOS, and web) using the same code. For this study, we mainly focused on the Android platform, which ensures compatibility with a wide range of devices commonly used by participants. It is currently compatible with Android versions from Android 7 (API level 24) and higher, ensuring consistent performance and reliable data acquisition regardless of the device manufacturer. These development specifications were defined to ensure the robustness, reliability, and reproducibility of the data collection process, which is essential for subsequent preprocessing, analysis, and model building.

Survey on Mobile Device usage Habits

To better understand the device usage habits without being invasive to the user, a daily survey was designed, which must be answered for a period of 14 days. It consists of 6 questions related to users' mobile device usage habits. The questions included in the survey are the following:

1) Approximately, how much time did you spend on social networks today? [24]
2) What kinds of Apps did you use the most in the last 24 hours? [25]
3) What networks have you used in the last 24 hours? [24]
4) What emotions did you feel while using social networks? [26]
5) What content did you mainly consume on social networks? [27]
6) How much did you agree or disagree with the information you found on social networks? [28]

The data collected through this survey allows us to obtain data on user interests and behavior patterns from their interaction with the content they access through their mobile device. The design of the survey was performed by considering prior studies addressing mobile usage and user experience, turning it into a valuable resource to correlate with the results derived from data acquired in other ways

B. Data Collection

This section describes the process for data collection, using the previously described tools and instruments. For this purpose, the steps followed by the data within the proposed methodology using the mobile devices are detailed (Fig. 1). It should be noted that prior to the start of the study, the protocol was approved by the Ethics Committee of the Institution where the study was carried out. All participants were informed about the use of their data and signed an informed consent form provided by the ethics committee.

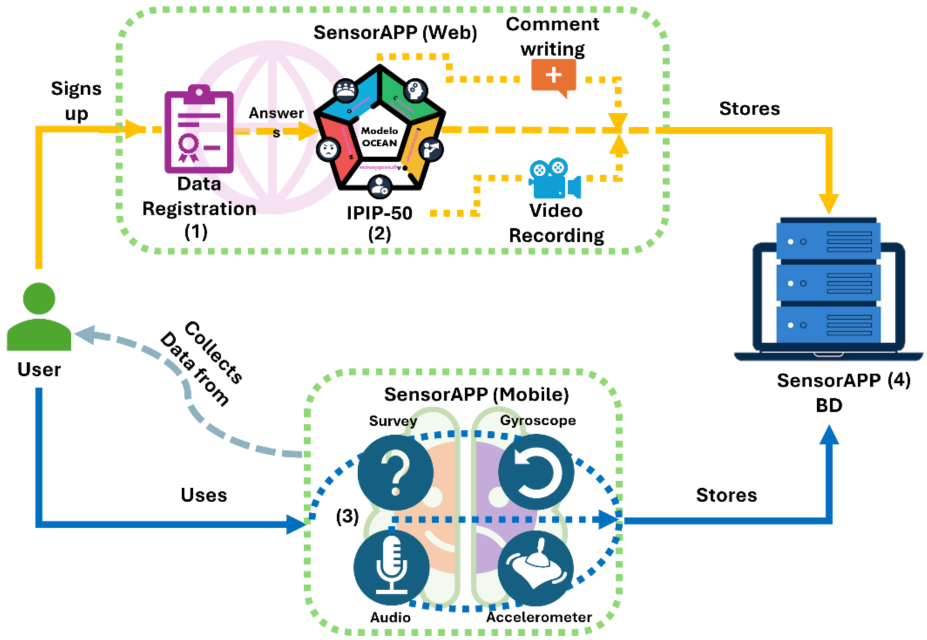

Fig. 1. SensorApp workflow to collect OCEAN personality data and signals from mobile sensors.

The collection process starts with the registration of the user in the SensorApp web platform. (1) For this, the user provides basic identification data (name, control number, email). This information is used to guarantee the quality of information gathered during the process. The user then accesses the IPIP-50 test to retrieve the reference data of the user's unique characterization on the OCEAN scale (2). Once these actions are completed, the user installs SensorApp Mobile on their Android device and performs the daily survey for a period of 14 days (3). During this period, data is also obtained from cell phone sensors (accelerometer and gyroscope). It should be noted that the data from the sensors are not collected continuously. This information is only collected during the moments in which the user responds to the daily survey, to obtain data from a significant period as a sample. All data collected from the workflow application are automatically stored in a non-relational database using Google Firebase services (4). The resulting stored dataset contains both quantitative (sensor measurements) and qualitative information (questions about emotions and social media activity).

C. Architecture

The software component, along with their externally visible properties, and the relationships between them constitute the fundamental elements of software architecture. For the development of this work, client-server architecture was implemented, both in mobile and web modes. The SensorApp architecture (Fig. 2) includes, in the presentation layer, the web and the mobile applications. On the server-side, it is composed of an application logic layer and a data layer. The logic layer can be divided into two parts: one corresponding to the web application and the other one to the mobile application. The logic layer of the mobile application contains separate modules for collecting data from sensors (gyroscope, accelerometer, and microphone), as well as a questionnaire that the user must answer, which is designed to record usage habits. On the other hand, the following components are found in the logic layer of the web application

- **Access control:** Records the user's login historical data and manager their authentication.
- **Comment:** Captures the text entered by the user. The instrument consists of 50 items, distributed across five personality dimensions, with 10 items per dimension. Each item is rated on a 5-point Likert scale. Thus, the maximum score per trait is 50, which is then normalized to a range between 0 and 1.
- **Video:** Allows video recording of the user while answering auxiliary questions designed to extract additional personality attributes.

Finally, the data layer (shared by both branches of the logic layer) consists of a non-relational database hosted in Firestore, a service provided by Firebase. This database stores information distributed across different collections (e.g., users, accelerometer, gyroscope, among others).

D. Data Processing

Data processing is a fundamental step in studies involving large or heterogeneous datasets, especially when information is collected from multiple sources, such as mobile devices. This stage comprises a number of techniques and procedures designed to guarantee that the data is suitable for analysis, improving quality, consistency, and reliability. In the context of personality recognition, proper data processing is essential for extracting meaningful patterns that help infer the attributes that characterize each individual. To achieve this, the raw data obtained from SensorApp (both in the mobile and web versions) underwent a preprocessing phase designed to transform it into a structured and consistent format (Fig. 3). This transformation reduces issues such as noise, missing values, and inconsistencies, which are common in mobile source data, and simplifies subsequent interpretation and modeling. In addition,

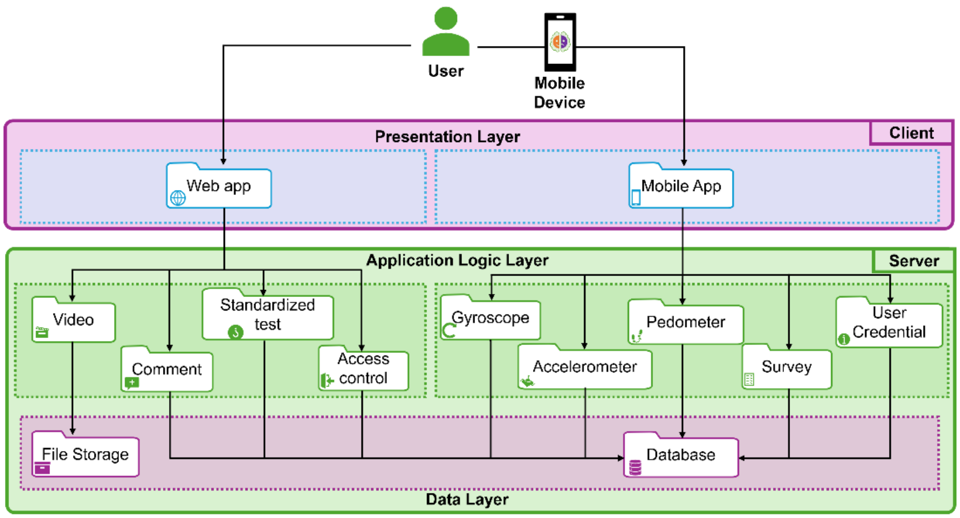

Fig. 2. Client-Server Architecture for SensorApp System, displaying three main layers (Presentation, Application and Data).

data validation and quality control were ensured using the standardized IPIP-50 personality test, a psychometrically validated instrument widely used in psychological assessment.

The dimensions of the OCEAN model were obtained directly from the IPIP-50 responses following standard scoring procedures. These data will be used as labels to estimate users' OCEAN values by creating a correlation between their personality trait scores and their mobile device usage habits.

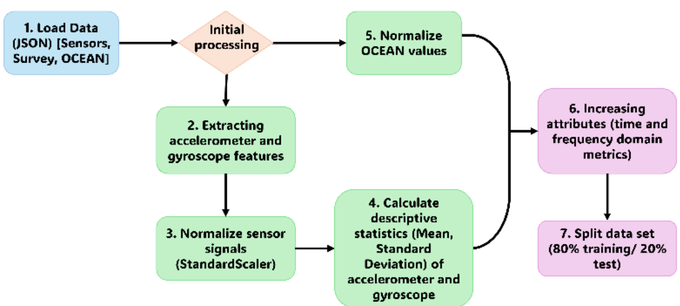

Fig. 3. Raw sensor data preprocessing and feature extraction methodology.

The data preprocessing stages are as follows:

1) **JSON file upload:** data stored in a JSON file containing sensor measurements of accelerometer, gyroscope, survey responses and OCEAN personality values of the test subjects were uploaded.
2) **Feature extraction:** relevant features related to the sensors (movements in X, Y, Z axis) were extracted.
3) **Normalization of sensor signals:** the movement data in the 3 spatial axes were normalized using StandardScaler, allowing the variables to have a homogeneous scale.
4) **Calculation of basic descriptive statistics:** the basic statistics (mean and standard deviation) of the sensor measurements were calculated for both the accelerometer and the gyroscope.
5) **Normalization of OCEAN values:** OCEAN values were normalized by rounding them to the first decimal place to maintain consistency in their presentation.
6) **Attribute augmentation:** data were augmented by calculating additional statistical metrics. These statistics fall into the time domain and the frequency domain of the sensor measurements. These attributes are justified in more detail in the next section.
7) **Set division:** the set was divided into 2 sets (training set and test set). These were divided with 80% of the data for the training set and 20% for the test set.

Feature Extraction

After the processing stage of data obtained from sensors on mobile devices, auxiliary measurements were calculated and subsequently added to the dataset as attributes, to enrich the previously processed dataset. These attributes are divided into two categories, which correspond to the domain in which the signals are analyzed, which are time domain attributes and frequency domain attributes. The time domain attributes are calculated from the time series of the sensor signals, giving the perspective of how the acceleration and angular velocity vary over time. Whereas the frequency domain attributes are derived to reveal the frequency components of which the sensor signals consist of. These attributes were selected for their potential to enrich the previously established dataset, allowing them to capture different aspects of the user's behavior that could present a direct correlation with his personality traits.

A) Time Domain Attributes

Time domain analysis examines sensor signals directly as a function of time, looking for properties that vary over the length of the period in which the samples were taken. The following attributes are calculated for each axis (x, y, z) of both accelerometer and gyroscope, by capturing relevant behavioral patterns. It should be noted that the attributes were calculated for each of the movements on the axes individually. The attributes calculated to add to the dataset:

- **Variance:** Fundamental measure of the dispersion of a dataset with n samples around its mean value (μ) for analyzing accelerometer and gyroscope signals. This allows measurement of the degree of dispersion of individual values with respect to the mean, which is computed as follows:

$$S^2 = \frac{\sum_i (x_i - \mu)^2}{n-1} \quad (1)$$

where x_i refers to the specific individual sample value within the analyzed window, and n corresponds to the total number of samples.

- **Interquartile range (IQR):** A measure of statistical dispersion representing the difference between the 75th percentile (Q3) and the 25th percentile (Q1) of a dataset (2), the IQR is defined as:

$$IQR = Q3 - Q1 \quad (2)$$

where Q1 and Q3 were calculated using linear interpolation (as implemented in the *Numpy* library). This method computes a weight-average value between consecutive data points when the quartile index does not match with a specific sample.

- **Root Mean Square (RMS):** A statistical measure used to quantify the magnitude and power of the sensor signal. It is calculated as the square root of the arithmetic mean of the squared values (3). For a discrete sequence of n samples, the RMS is defined by the following expression:

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \quad (3)$$

where x_i represents a specific sample, and n is the total number of samples in the analyzed window.

- **Entropy:** Measure of randomness and uncertainty in a variable, quantifying the unpredictability of changes in the signals (4).

$$H = -\sum_i^n P_i \, log_2(p_i) \quad (4)$$

where n represents the total number of possible outcomes in the signal's distribution, i is the index that iterates through these outcomes, and p_i is the probability of that specific outcome occurring.

B) Frequency Domain Attributes

Frequency domain analysis involves transforming data collected from time domain sensors to the frequency domain. This is performed to examine the frequency components of the signals. This allows us to examine patterns in the movements that may be missed by those attributes in time domain. The following measurements will be calculated in the frequency domain for each axis of the accelerometer and gyroscope in defined time windows. These attributes are:

- **Discrete Fast Fourier Transform (DFTT):** This algorithm calculates the Discrete Fourier Transform (DFT) by decomposing a sequence of values into components at different frequencies (5). By applying this calculation to the accelerometer and gyroscope signals, the amplitude of each frequency component present in the movements can be analyzed, as follows:

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi kn/N} \quad (5)$$

where $X(k)$ denotes the frequency component k in the frequency domain, while $x(n)$ represents the discrete-time input signal from the sensors. Parameter N defines the total number of samples within the analyzed window, k is the frequency index (ranging from 0 to N-1), and j is the imaginary unit (where $j^2 = -1$). This decomposition allows the identification of dominant frequencies and spectral power associated with specific physical activities.

- **Discrete Cosine Transform (DCT):** It is a transform directly related to the DFT, expressing a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies (6), which is defined as:

$$X(k) = \alpha(k) \sum_{n=0}^{N-1} x(n) \cos\left(\frac{\pi(2n+1)k}{2N}\right) \quad (6)$$

where $x(n)$ denotes the discrete signal input from the sensors, N is the total number of samples in the window, and n is the sample index. The scaling factor $\alpha(k)$ ensures the transformations are orthonormal

- **Energy:** this is calculated by adding the squares of the magnitudes of its frequency components obtained through the DFFT. This is a general indicator of the level of activity, where a higher energy in the frequency spectrum indicates a higher power in the movements (7), which is computed as:

$$E_x = \sum_{n=-\infty}^{N-1} |x[n]|^2 \quad (7)$$

where E_x denotes the total energy of the signal for a specific axis, $x[n]$ represents a discrete sample of the sensor's signal, and N is the total number of samples in the analyzed window.

- **Power Frequency Range (PFR):** This metric represents the range of magnitude within the frequency spectrum, calculated as the difference between the maximum and the minimum amplitudes of the signal's components (8), as follows:

$$PFR = \max(|X(k)|) - min(|X(k)|) \quad (8)$$

where $|X(k)|$ denotes the magnitude of a specific reading in the frequency component. This parameter characterizes the intensity distribution of the movement, where a higher range indicates the presence of dominant frequency peaks to the noise floor or minimum activity levels.

E. Neural Network Selection

According to the data collected from the use of mobile devices and standardized tests, the way of processing data is as important as the choice of networks to be used to train and subsequently make predictions of personality recognition in this particular case. For this work we considered diverse neural network architectures representative of the realm of deep learning. First, a Multi-Layer Perceptron (MLP) with 1 hidden layer and ReLU activation function was considered. MLPs are densely connected models that allow us to model very complex functions [29]. Secondly, a Convolutional Neural Networks (CNN) with 2 convolutional layers was considered. The motivation to use CNN is that it accounts for the spatial information in time series [30]. Next, a sequential model, Long Short-Term Memory (LSTM), was adopted. This model was included because we wanted to explicitly model sequential information available in the input data [31]. Last, but not least, a transformer model [32] of 2 dense layers was included in the comparison. Transformers are representative of attention-based models that have succeeded recently in a number of domains.

F. Experimental Setup and Computational Environment

We defined a standardized computational environment to train and evaluate the machine learning models to guarantee the validation and replicability of the experiments. We used Google Colaboratory (Colab) cloud notebook environment, on the Google Cloud Platform (GCP) infrastructure to execute the training and validation processes of the machine learning models. To optimize data processing and training efficiency, we used GPU acceleration, selecting the standard "Python 3, GPU accelerated" runtime provided by Colab. The dynamically allocated hardware consisted of an NVIDIA Tesla T4 Graphics Processing Unit (GPU), with 15 GB of video memory (VRAM), and an Intel Xeon Central Processing Unit (CPU) operating at 2.3 GHz, supported by 12 GB of RAM. Software dependencies, including TensorFlow/Keras and Scikit-learn, were managed using Colab's pre-installed libraries, ensuring a standardized and reproducible environment for running the experiments.

IV. Experiments and Results

This section details the experiments performed with the objective of predicting users' personality attributes using the resulting dataset from the SensorApp mobile and web application (sensors and IPIP-50) in combination with the added features using different statistical metrics. Prior to evaluating predictive models, an unsupervised clustering of accelerometer and gyroscope features was performed to identify natural groupings among users. Personality traits from the IPIP-50 were overlaid on the cluster space to explore preliminary links between activity patterns and personality profiles. Next, based on the data collected, four neural network architectures (MLP, CNN, LSTM and Transformer) were trained and evaluated. The experiments were designed to analyze the performance of the models on the personality trait estimation task, considering standard predictive model evaluation metrics (loss, MAE & MSE). The results obtained by each of the architectures are compared, seeking to identify which type of network offers the best performance according to the specific characteristics of the data used.

A. Beta-testing Phase

A preliminary beta-testing phase was conducted to verify the technical feasibility and workflow of the SensorAPP system [33]. This initial stage was carried out with a group of nine senior college students (seven men and two women) from a university in Mexico. The protocol consisted of a linear self-reporting approach where users installed the APK application on Android devices and were asked to respond to a usage habits survey once a day for a period of 14 days. To ensure proper compliance, the application sent two daily reminder notifications. The students reported no failures or difficulties in performing the test within the application, enabling the next phase of large-scale experiments with the already validated platform.

B. Sample Group

The criteria to include participants in this study was based on a standard population of young technology users selecting them by convenience sampling. A total of 126 senior college students at a university in Mexico were selected. No health criteria were used so no clinical diagnoses were considered. The average age of the participants was 22.4 years, and there were 94 males and 32 female participants. Of the 126 participants, only 16 completed the entire program with three activities: register their IPIP-50 personality profile on the web platform, answer the questionnaire, and collect sensor data on the mobile app. This core analysis group of 16 participants, comprising 11 men and 5 women, generated a total of 160 records. The remaining 110 participants completed only part of the scheme. Specifically, 52 participants only responded to the IPIP-50 test on SensorApp Web, and 58 participants used only the mobile app, generating 198 records.

C. Unsupervised Analysis of Sensor Data

To better understand user behavior, we analyzed the distribution of individuals according to their dominant personality traits using the OCEAN model. Fig. 4 shows a visualization based on the users' movement features.

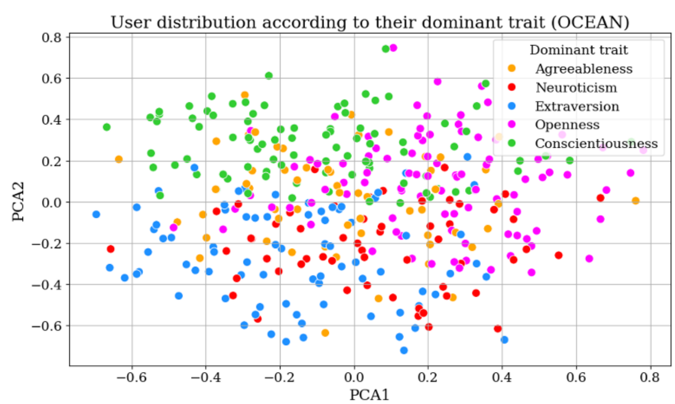

Fig. 4. User distribution according to their dominant personality trait.

Where each point represents an individual, showing their dominant trait. This initial distribution shows how personality profiles are distributed in a reduced-dimensional space. Although there's no exactly defined grouping, the figure reveals a dispersion pattern that suggests overlapping characteristics among users with different dominant traits.

To examine the relationship between personality traits and behavioral patterns on a closer manner, acceleration data was analyzed from mobile sensors. In Fig. 5 a two-dimensional density map is shown where each point represents a user's movement, and the color indicates their dominant personality trait. While most users fall in a central, high-density region, subtle spatial variations emerge. For example, users with conscientiousness as dominant trait tend to concentrate in the upper-central area, while users with neuroticism as dominant trait show broader dispersion. These patterns suggest that despite shared core behaviors, there may be trait-specific differences in physical activity.

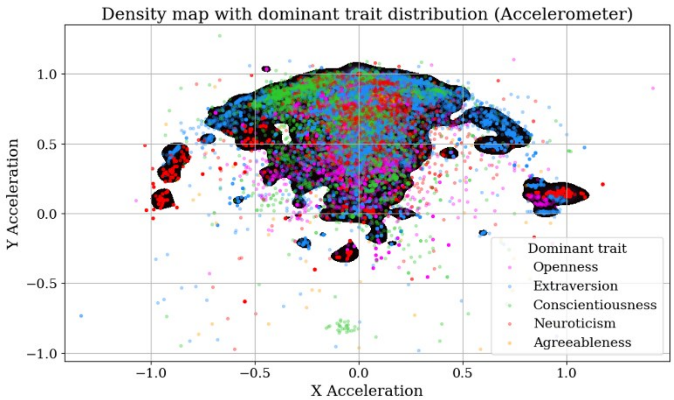

Fig. 5. Density map for accelerometer movement with dominant trait distribution.

Meanwhile, Fig. 6 is a density map of gyroscope data displaying device rotation on the X and Y axes. Most of the data points are tightly clustered near the origin, which indicates that the rotational movements are generally subtle and consistent across all users.

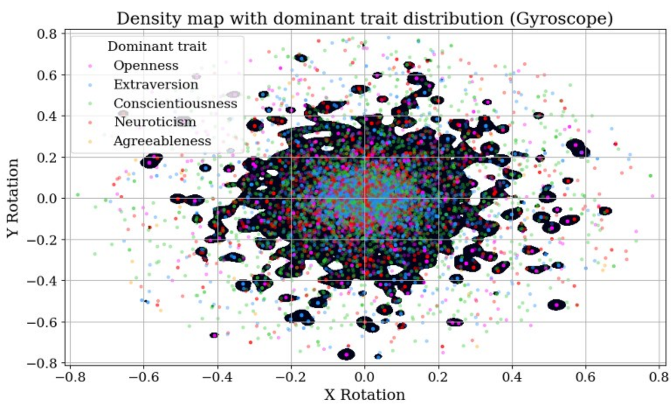

Fig. 6. Density map for gyroscope movement with dominant trait distribution.

The analysis of sensor data revealed distinct patterns across modalities. While accelerometer data showed moderate differentiation aligned with personality traits, gyroscope exhibited highly centralized behavior with minimal variation. These results suggest that gyroscopic behavior is less influenced by personality traits during typical device use, whereas acceleration may capture more nuanced behavioral expressions.

D. Experimental Settings

Before setting up the experiments, the data was carefully prepared. First the data was split into training and test sets. Specifically, the normalized dataset and personality traits were segmented into four distinct sets (features and labels for training and features and labels for evaluation). For evaluation, the size of the test set was set at 20%, while the remaining 80% was used for training. Subsequently, the hyperparameter configuration for the different neural networks were defined. First, an MLP was defined (Table I), this was built with 3 dense layers. An input layer with 64 neurons and ReLU activation function, a hidden layer with 32 ReLU neurons and a linear output layer with 5 neurons representing the dimensions of the OCEAN model (criterion that will be kept constant in the 4 test networks). The model was optimized with Adam and trained for 100 epochs with a batch size of 8 parameters.

TABLE I
HYPERPARAMETERS AND ARCHITECTURAL LAYER CONFIGURATION FOR THE MLP MODEL

Layer	Layer Type	Neurons	Activation	Function
Input	Dense	64	ReLU	Initial feature processing
Hidden	Dense	32	ReLU	Intermediate pattern extraction
Output	Dense	5	Linear	Personality trait prediction

For the experiments with the CNN network (Table II), two convolutional layers with pooling were defined, followed by a Flatten layer, a dense layer and an output with 5 linear neurons. The model was compiled with the Adam optimizer and trained for 100 epochs with a batch size of 8 parameters.

TABLE II
HYPERPARAMETERS AND ARCHITECTURAL LAYER CONFIGURATION FOR THE CNN MODEL

Layer	Layer Type	Parameters	Activation	Function
Input	Conv1D	64 filters	ReLU	Local pattern extraction
Pooling	MaxPooling	Pool size: 2	—	Dimensionality reduction
Conv1D	Conv1D	32 filters	ReLU	Pattern refinement
Pooling	MaxPooling	Pool size: 2	—	Further dimensionality reduction
Flatten	Flatten	—	—	3D to 1D structure conversion
Dense	Dense	64 neurons	ReLU	Dense representation
Output	Dense	5 neurons	Linear	Prediction of the five personality traits

Regarding the experiments performed with LSTM (Table III), for these one two contiguous LSTM layers were established, the first one with 64 neurons returning sequences, which allows the second layer of 32 units to process the sequential information extracted by the previous layer. This is followed by a dense layer of 16 neurons with ReLU activation that transforms and reduces the extracted features. To finish with a linear output layer of 5 neurons. The model was compiled with the Adam optimizer, training for 100 epochs with batches of 8 parameters.

To finalize the definition of the networks, a Transformer network was created (Table IV), whose architecture is composed of a transformer block that integrates multi-head attention, dense feedforward networks (FFN), normalization of the dropout layers to improve stability and avoid overfitting. After the transformer block, a global pooling is applied to reduce the dimensions, to continue with two dense layers with ReLU activation function to refine the information, ending with a 5-neuron linear output. The model was compiled with the Ada optimizer, using 100 epochs with a batch size of 8 parameters.

TABLE III
HYPERPARAMETERS AND ARCHITECTURAL LAYERS CONFIGURATION FOR THE LSTM MODEL

Layer	Layer Type	Parameters	Activation	Function
LSTM 1	LSTM	64 units	—	Sequential pattern extraction
LSTM 2	LSTM	32 units	—	Processing sequence from previous LSTM layer
Dense	Dense	16 neurons	ReLU	Feature transformation and dimensionality reduction
Output	Dense	5 neurons	Linear	Prediction of the five personality traits

TABLE IV
HYPERPARAMETERS AND ARCHITECTURAL LAYERS CONFIGURATION FOR THE TRANSFORMER MODEL

Layer	Layer Type	Parameters	Activation	Function
Input	Input	(1, number of features)	—	Sequence of length 1 containing all features
Transformer	Custom Transformer Block	4 heads, FFN with 32 neurons	—	Multi-head attention, transformation, and normalization
Pooling	GlobalAvera gePooling1D	—	—	Dimensionality reduction
Dense	Dense	32 neurons	ReLU	Intermediate transformation
Dense	Dense	16 neurons	ReLU	Feature refinement
Output	Dense	5 neurons	Linear	Prediction of personality traits

E. Experimental Results

By testing with the previously established neural network models (MLP, CNN, LSTM and Transformer) and with the dataset obtained from SensorApp data collection (mobile sensors, IPIP-50 responses, time and frequency domain statistics, SensorApp survey). The comparison was performed in 2 different modalities:

1) Using only daily survey responses and movement captured by the sensors.
2) Incorporating both statistical metrics and sensor and survey data.

Looking at Table V, it can be concluded that in using the sensor data and the daily survey, the CNN network shows the best performance, with an MSE of 0.0605 and an MAE of 0.1961. Indicating that this type of network is effective in capturing data patterns in movements and predicting personality traits with good accuracy. The Transformer, although it proved to be slightly less accurate (MSE = 0.0712 and MAE = 0.2209), is a viable option for performing this type of testing. As the LSTM, since it shows values quite close to those obtained by the Transformer with an MSE of 0.0721 and a MAE of 0.2207, it still fails to outperform the previous architecture in any of the two-evaluation metrics. The MLP is the one that obtained the least favorable values (MSE = 0.1144 and MAE = 0.2867), it is estimated that this is due to the simplicity of its architecture compared to the other specialized models for more complex tasks

While in the sensor tests and daily survey adding the attribute values of the statistical values in time and frequency domain, the results show a similar trend, with interesting changes to consider. Since in this case the Transformer model achieved the best accuracy, performing well with an MSE of 0.0513 and a MAE of 0.1704. Making it the most accurate option, above CNN, which, although it performed well with an MSE of 0.065 and a MAE of 0.1766, lags slightly behind Transformer. While both LSTM and MLP both achieved MSE scores close to 0.06, they had MAEs close to 0.195, which makes them better suited for tasks with a larger amount of data. These results suggest that the use of additional metrics extracted from the time and frequency domain significantly improves the performance of the models.

TABLE V
MSE AND MAE RESULTS OF TESTS WITH NEURAL NETWORKS

Model	MSE (Sensors + Survey + Statistics)	MAE (Sensors + Survey + Statistics)	MSE (Sensors + Survey Only)	MAE (Sensors + Survey Only)
MLP	0.0603	0.1956	0.1144	0.2867
CNN	0.0650	0.1766	0.0605	0.1961
LSTM	0.0601	0.1935	0.0721	0.2207
Transformer	0.0513	0.1704	0.0712	0.2209

To evaluate the performance of the developed models on the personality trait prediction task, a K-Fold cross-validation was implemented on each of the networks (Table VI). This technique allows a robust estimation of the generalized error when training and evaluating the models on different partitions of the dataset. The results show that the CNN network presents the best overall performance with an average MAE of 0.1689 and an average MSE of 0.0511, presenting the lowest values in both metrics. The Transformer model also demonstrated good performance, with an MAE of 0.1738 and an MSE of 0.0528, outperforming the LSTM and MLP architectures. These both achieved an average MAE close to 0.194 and an average MSE of approximately 0.06, presenting the lowest values in the cross-validation.

TABLE VI
MAE AND MSE RESULTS OF K-FOLD CROSS-VALIDATION

Model	Average MAE	Average MSE
CNN	0.1689	0.0511
Transformer	0.1738	0.0528
LSTM	0.1932	0.0608
MLP	0.1936	0.0601

V. CONCLUSIONS AND FUTURE WORK

This section presents the conclusions drawn from the experiments performed with the various neural network architectures previously established, using the data obtained from the SensorApp experiments. It also discusses possible future work related to the development of this work.

A. Conclusions

The results of this study demonstrate that personality traits within the OCEAN model can be accurately predicted using a multimodal framework that integrates mobile sensor data, survey responses, a time-frequency features. Our Transformer model achieved the best performance (MSE = 0.0513, RMSE =

0.2265, and MAE = 0.1704), outperforming recent regression-based approaches such as that of Gao et al. [19], who employed a multi-view multi-task deep learning framework for personality detection and reported error rates ranging from 0.256 to 0.510 for MAE and 0.305 to 0.647 for RMSE. The observed improvement in predictive accuracy and robustness can be attributed to heterogeneous data source integration and advanced deep learning architectures, which enables comprehensive characterization of personality traits under realistic conditions. Results from cross-validation further support the proposed models' stability and generalization. Despite these promising results, certain limitations were identified, mainly related to user retention during the data collection process. Participant dropout and privacy concerns reduced the effective sample size, although the final dataset was sufficiently large to complete the experimental evaluation. Therefore, future work should focus on increasing the sample size and diversity to strengthen generalization. To address these challenges, the adoption of incentive mechanisms, gamification strategies, and improved anonymization techniques is recommended. In addition, future work will consider expanding the dataset using generative AI techniques and incorporating new sources of contextual information to further improve predictive performance.

B. Future Work

As part of a future development for the project, it is considered to expand the number and diversity of participants, with the objective of continuing to create a more robust and complete dataset. Also, the inclusion of new information to be used in the training of the networks is being considered, such as the use of users' writings and voice audio, for which Natural Language Processing (NLP) will be used. The data provides complementary information to improve the prediction of personality traits. Similarly, the exploration of more machine and deep learning models is planned, to find the most suitable for the task of predicting the unique characterization of personality. Likewise, new approaches will be sought to make the data collection process more attractive to the user and to complete the scheme of record in most cases. Furthermore, for future iterations, we will focus on conducting individual analyses of the importance of each attribute in the dataset, including both sensor variables and self-reported variables in order to provide a comprehensive insight into their relative contributions to automatic personality recognition using mobile usage habits data.

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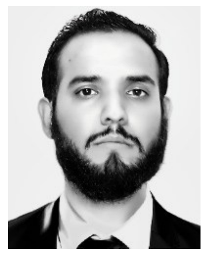

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