

Retraction

Retracted: Prediction and Influencing Factors of Big Data on College Students' Positive Psychological Quality under Mobile Wireless Network

Mobile Information Systems

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] L. Jiang and Y. Zhang, "Prediction and Influencing Factors of Big Data on College Students' Positive Psychological Quality under Mobile Wireless Network," *Mobile Information Systems*, vol. 2022, Article ID 4344747, 11 pages, 2022.

Research Article

Prediction and Influencing Factors of Big Data on College Students' Positive Psychological Quality under Mobile Wireless Network

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Psychological big data is observed based on behavior or habitual features of people for determining the influencing factors. The influencing factor information is used for analysis in treatment, recommendation, and diagnosis of psychological disorders, depression, etc. Identifying the influencing factors is challenging due to irregular behaviors and responses from young people. However, for organizing the quality of observation, this article introduces a behavioral pattern recognition method (BPRM) with associating quality (AQ) identification. This method observes the different day-to-day behaviors of young people and recurrently associates them. The observations are aided through conventional wireless networks for swift interconnection and information sharing. The association is organized based on the transfer learning state processing model. Based on the state processing, the behavior-based psychological data are classified as abnormal and normal. If the association throughout the state changes remains the same, then it is organized or else the new data are identified as an influencing factor. The state changes are validated using random observation intervals that result in series data associations. Based on the actual data extraction, the proposed method improves the prediction accuracy and reduces false rate and processing time, whereas it improves the organization precision.

1. Introduction

Psychological quality assessment is a process that is used to perform a comprehensive assessment to evaluate the tasks and needs. Psychological quality assessment is used to find out the mental health condition such as capabilities, behaviors, uniqueness, and personality of a person [1]. The psychological quality assessment process conducts tests and finds out the quality of the person. The psychological quality assessment process is mostly used in colleges to identify student's mental states [2]. Individual and group tests, intelligence tests, and paper and pencil tests are some of the psychological assessment tests that are available for youths. The test is also used to find out the depression rate, fear rate, and personality rate of college students [3]. The main characteristics of psychological quality assessment of students are to provide an optimal set of details for various

educational activities. Universities and colleges conduct assessment tests for students and give admission to the best students [4]. A psychological quality assessment provides a satisfactory set of data for an administration that reduces the problems on the college campus. Students' psychological assessment reduces error and problem rates in the prediction process. This increases the accuracy rate in the behavior detection process, which enhances the performance of the system [3, 5].

Big data is a collection of data that contains a huge amount of data. The big data analytic process provides various methods for data analysis process that reduces error rate and complexity rate in analyzing process. Big data is used as a data mining process that finds out the necessary data from a large amount of data [6]. The big data analytic process is mostly used for identifying data from a large number of datasets and producing an optimal set of data for

the further process [7]. Data are generated from machine data, social data, and transactional data. The big data analytic process is widely used in the psychological quality assessment process that contains numerous numbers of datasets. The major impact of big data in psychological quality assessment is to collect data and perform analysis process at need time to reduce the latency rate in the computation process [8]. The big data analytic process reduces the error and risk rates in the classification and identification process. The psychological assessment identifies the personality, behavior, and mental state of people, and produces an appropriate set of data. The big data analytic process addresses risks and challenges that are presented in the psychological assessment system. In psychological quality assessment, big data analytics mostly identifies statistical data and psychological data for the further analysis process [9, 10].

Machine learning (ML) techniques are widely used in various fields that improve the accuracy rate in the detection, recognition, and analysis process. ML techniques are used in the psychological quality assessment process that enhances the performance and efficiency of the system [11]. The big data analytic process uses ML approaches to get a feasible set of data for further processes. The ML-based big data analytic process is mostly used for identifying the mental state and condition of people that provide necessary information for psychological quality assessment [12]. The data-driven ML approach is used in the big data analytic process that provides a better prediction process with a minimum error rate. The data-driven approach gets information from high-dimensional data and provides appropriate data for the analysis process [13]. A theory-driven computational approach is also used in the psychological big data analytic process. The theory-driven approach provides a multilevel analysis process that improves the accuracy rate in the detection and prediction process. The multilevel analysis process reduces the complexity and error rate in the identification process. The ML algorithm improves the statistical algorithms that are presented in the assessment process [14, 15].

2. Related Work

Wang et al. [16] introduced a danmaku emotion analysis method using the bidirectional long short-term memory (Bi-LSTM) approach. The proposed method is used for the emotion classification process that finds out the exact emotion of people. Emotions such as anger, sorrow, happiness, sadness, and pleasure are identified and analyzed by the danmaku emotion analysis method. The proposed method increases the accuracy rate in the emotion classification process, which enhances the performance and efficiency of the system.

Zhang and Luo [17] proposed a data mining-based analysis process for psychological education. Both computer hardware and software are collaborated here to form an effective method for the identification process. The data mining technique is used here to find out the details and features of students' psychological information. Pattern recognition is also used in the proposed method to find out

the exact condition of students. The proposed technology improves the effectiveness rate in the psychological education system.

Maeda et al. [18] introduced a new analysis method for behavioral and psychological symptoms of dementia (BPSD). The self-assessment scales are first identified and collected for the analysis process. The feature extraction process is used here to find out the important features and patterns of information and produce a final set of data for the behavior analysis process. The proposed BPSD method increases the accuracy rate in the identification process, which improves the feasibility and reliability of the system.

Contreras et al. [19] introduced a prediction method for quality of life (QoL) in family care. A multiple regression analysis process is used here to find out the important patterns and features of family members. Psychological inflexibility is the only concern that affects the performance rate in QoL. The proposed method decreases the inflexibility rate and provides an appropriate set of data for the prediction process. The proposed prediction method reduces the error rate in the prediction process, which increases the efficiency and effectiveness of family care.

Szarko et al. [20] proposed an acceptance and commitment training (ACT)-based prediction method for psychological flexibility in the medical education system. The proposed method predicts the accurate ACT of students and provides a proper set of data for the further analysis process. Psychological flexibility is used as a burnout tool in medical education that produces actual details. The proposed method improves the accuracy rate in the prediction process and reduces the latency rate in the computation process.

Fabero-Garrido et al. [21] introduced a delayed-onset muscle soreness (DOMS) and daily activity (ADL) prediction method for psychological assessment. Negative psychological factors are first identified using certain patterns. Distress, strength, and catastrophizing are some of the patterns that are identified by the proposed method. A visual analog scale (VAS) is used here to find out the intensity rate of psychological factors. The proposed method improves the feasibility, scalability, and reliability of psychological assessment by increasing the accuracy rate in the prediction process.

Radia et al. [22] proposed a conceptual model to identify customer experience on psychological comfort (PC). The proposed method finds out the customer intentions and relationship quality of customers that produce an optimal set of data for the analysis process. Relationship quality plays a vital role in PC that improves the performance and feasibility of the system. The proposed conceptual model increases the accuracy rate in PC, which reduces the latency rate in the computation process.

Hsieh et al. [23] introduced a comprehensive framework that identifies the online brand community participation in psychological empowerment. The proposed framework finds out the user satisfaction rate over psychological empowerment. Both patterns and behaviors of users are identified and produce a final set of data for the analysis process. The proposed framework improves the reliability and efficiency rate of the online psychological empowerment system.

Pan et al. [24] proposed a psychological decision-making model for parking and the noncomputing travel mode is used here to provide the necessary set of data for the analysis process. Features such as awareness, coping plan, action plan, and behaviors of users are identified by noncomputing mode. User behaviors are identified by the proposed model that improves the accuracy rate in the decision-making process. The proposed decision-making model increases the effectiveness and feasibility rate of the system.

Parent-Lamarche et al. [25] introduced a multilevel regression analysis process to identify psychological distress in the workplace. The hierarchical structure of employees is collected and used in the regression analysis process. Both personality and workplace environment are identified here that provide the necessary set of data for the analysis process. Experimental results show that the proposed analysis process improves the performance and reliability of the workplace environment.

Visser et al. [26] proposed a new psychological trajectory identification process using the latent class analysis process. The characteristics of trajectories are classified based on certain patterns and features. The proposed identification process provides actual health conditions and mental state of users that improve the accuracy rate in the analysis process. The proposed method improves the overall quality of life (QoL), which increases the efficiency rate of the system.

El-Yafouri et al. [27] introduced an acceptance model for the social and technical factor identification process in the electronic medical record (EMR) system. The proposed model identifies the behaviors of users using EMR. The proposed model produces an optimal set of data for both decision-making and data analysis process. Experimental results show that the proposed model increases the accuracy rate in the identification process, which improves the feasibility of the system.

Yang and Liu [28] proposed a dynamic monitoring system using a big data analytic process for the mental health of vocational students. Big data finds out the necessary details from the huge amount of data that reduces the latency rate in the identification process. The proposed system monitors the activities of students and finds out the anomalies using the analysis process. The overall accuracy rate in the detection process is increased and provides relevant information for the analysis process.

3. Proposed Behavioral Pattern Recognition Method (BPRM) with Associating Quality (AQ) Identification

The proposed BPRM with associating quality (AQ) identification method is designed to observe psychological big data based on behavior and habitual features of college students/young people for determining better-influencing factors in behavior analysis. The influencing factors such as recommendation, treatment, depression, and diagnosis of psychological disorders are consecutively observed by the BPRM method. It ensures the irregular behaviors and

responses from college students and based on this identification outputs for different young people at different time intervals. The BPRM function is presented in Figure 1.

The process of irregular behaviors and response detection is observed from acquired college student information-based behavior data association. In a college student's behavior analysis, the different day-to-day behaviors and responses of young people are jointly analyzed and recurrently associated with them through conventional wireless networks. Therefore, this wireless network is responsible for behavior observation and information sharing in an organized manner with less false rate and processing time. The data association is modeled for the state changes in prediction and influencing factors of big data on college students. The data association is reliable to be employed for another state within the same wireless network at any interval. The objective of this method is to maximize prediction accuracy and positive psychological quality under wireless mobile networks (Figure 1). The psychological data observation and behavior outputs based on the influencing factors' problem result in false rates. The abnormal quality of college student's behavior data analysis is impacted by this false rate; then,

$$\sum_{a=b} (\text{Psy}_d, \text{Beh}_d)_{ob} = \sum_{ob=t} \left[(\text{Psy}_d)_{oba} - 1 - \left(\frac{(\text{Psy}_d)_b}{\prod (\text{Psy}_d + \text{Beh}_d)_a} \right) \right], \quad (1)$$

where the variables $(\text{Psy}_d, \text{Beh}_d)$ represent the psychological data and behavior observation from college students/young people through a mobile wireless network from the prediction and influencing factors of big data b . The maximum positive psychological quality $Q = 1$ achieves high Psy_d and Beh_d for the analysis of influencing factors to the behavior or habitual features' observation. ob denotes the number of psychological data observations, and a represents the behavior pattern analysis sequences. Instead, b and t are not constant due to wireless networks for swift interconnection and information sharing as $Q \in [0, 1]$ is the differing condition. Therefore, $Q = 1$ is not observed in any time interval t , resulting in a false rate and irregular behaviors. This issue is referred to as influencing factors of big data on college students and day-to-day behavior analysis of young people. The assisting big data and transfer learning are jointly used in the proposed psychological quality analysis of maximum psychological behavior observation on college students.

3.1. Big Data-Based Psychological Quality Observation. In big data-based psychological quality observation, the student's behavior and habitual feature analysis are achieved by swift interconnection and information sharing through the wireless network. The behavioral pattern processing occurs under mobile wireless networks guided by the psychological big data. Figure 2 presents the observation sequence for different d from a data source.

The observed d is classified as shared patterns $\forall (\text{Beh}_p)$. This is required for identifying S_{ch} before f impact; the nonadversary impact creates different behavior models from which data extraction is performed. This extraction is

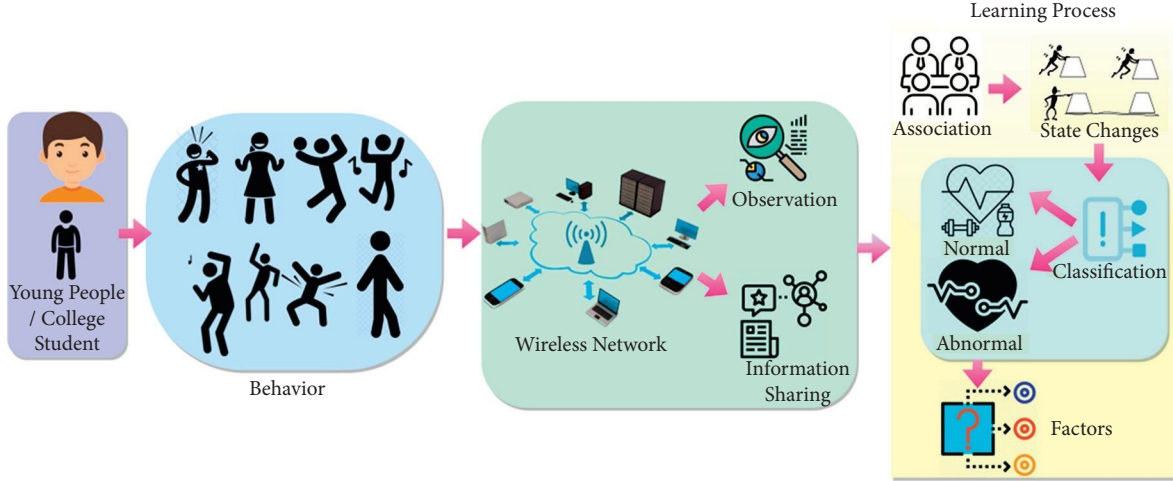
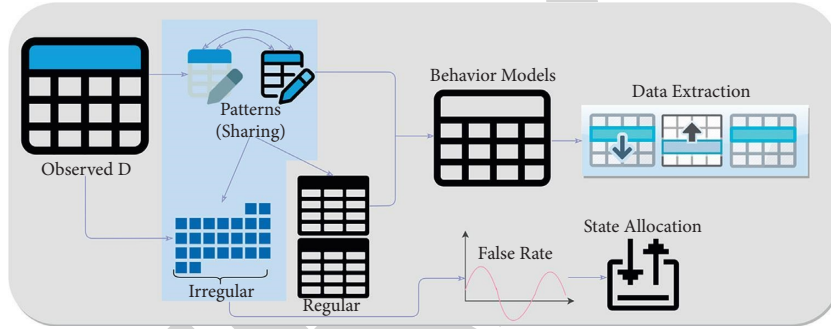


FIGURE 1: BPRM function.

FIGURE 2: Observation sequence for different d .

different for irregular inputs (d), wherein the false rate-causing instances are present. This requires state allocation learning for f mitigation. In Figure 3, the observed false rate and continuity under different time intervals are presented.

The above representations are provided from the dataset based on observation interrupts. The false rate is estimated as the difference in f_{ob} between the series and consecutive data provided. However, the above representation requires S_{ch} after the classification using transfer learning. Therefore, state allocation takes place (refer to Figure 3). The big data consists of observation and information sharing process to identify the irregular behavior and activity occurrence in the college students or young people, as in equation (1). The probability of behavioral patterns considered in t without false rate and irregular behaviors, i.e., $\rho(\text{Beh}_p)$, is given by the following:

$$\rho(\text{Beh}_p) = \frac{\sum_{ob \in t} f_{ob} ir^{-\text{Psy}_d/b.C_\alpha.ob}}{\sum_{a \in b} f_a} \quad (2)$$

In equation (2), the variables f_{ob} and f_a represent the false rate and irregular behavior analysis of b at any time interval t and the actual false rates or irregular behavior observations, respectively. Similarly, the false rates/irregular behaviors and responses based on the condition $1 - ((\text{Psy}_d)_b / \prod (\text{Psy}_d + \text{Beh}_d)_a)$ are computed using C_α . The

initial condition for maximizing the probability of psychological quality of data analysis $Q = 1$ is the influencing factor; this is the behaviors of college students; and therefore, the data association is performed based on the false rate observation $ob \in t$. The association of psychological data and acquired information of b in t aided to compute an output for both psychological and behavioral data analysis of college students. This false rate detection is estimated using

$$f_{ob} \forall ob \in t = \left[(1 - C_\alpha) \frac{\text{Psy}_d}{f_a} - Q \cdot \frac{\text{Psy}_d}{J} - (f_a - f_{C_\alpha}) \right], a \in b. \quad (3)$$

From equation (3), the false rate analysis of the available psychological b is identified through a conventional wireless network in t . If the condition $f_{ob} \forall n \in t$ is analyzed for data association that is organized, then state changes are required. Irregular behaviors and responses of big data maximize C_α , again facing the functions and observations of association. Big data holds the acquired data of Psy_d and behavior analysis of b as $\{Q, f, f_{C_\alpha}, \rho(\text{Psy}_d)\}$, after the psychological data observed or Beh_d analysis in t at any interval. The detection of the irregular behaviors and responses from college students based on Beh_d and $f_a \forall a \in b$ is analyzed by big data and is organized with the data association of the mobile wireless network. The output is accounted for as

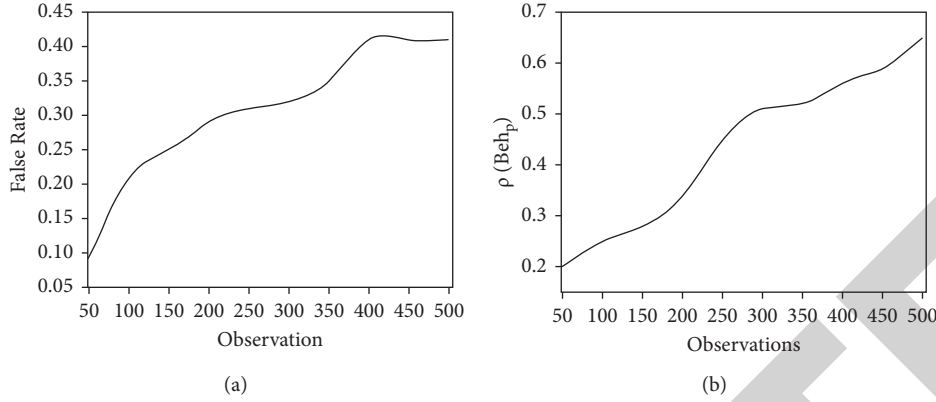


FIGURE 3: Observed false rate and probability of patterns.

influencing factors recurrently associated with them for observation and information sharing. In this method, the outputs are observed using behavioral pattern analysis and it relies on f and Q , based on the condition $\sum_{ob \in b} (\text{Psy}_d)_{ob} = \text{Psy}_d$ and f_{c_α} and $\rho(\text{Psy}_d)$ for the influencing factor in equation (1). Therefore, let Beh_t and Beh_{c_α} denote the data association of Psy_d in both conditions. It refers to the psychological quality of data observed and behavior pattern output for the college students based on prediction. Hence, the total state change (S_{ch}) is estimated as follows:

$$S_{ch} = \left(\frac{\text{Beh}_t * \text{Beh}_{c_\alpha}}{ob} \right). \quad (4)$$

Instead, this consecutive process observes the day-to-day behaviors and activities of college students and recurrently associates the data. Hence, equation (4) is substituted in both psychological data observation and behavioral pattern observation for the precise solution, respectively.

$$\text{Beh}_t = \sum_{ob \in b} (\text{Psy}_d)_{ob} = \frac{Q \sum_{ob \in t} (\text{Psy}_d)_{ob} / f_{ob}}{Q \sum_{a \in b} f_a}. \quad (5)$$

Here,

$$\text{Beh}_{c_\alpha} = \frac{\sum_{ob \in b} \sum_{a \in t} (\text{Psy}_d)_{oba} - (1 - \zeta_{\alpha oba})}{\sum_{ob \in b} (f_{ob} - f_{c_\alpha})}. \quad (6)$$

Based on equations (4), (5), and (6), S_{ch} is evaluated as an influencing factor of Psy_d and f with ζ_α to compute the precise output. Therefore, Beh_t relies on f and Q whereas the failure in the computation of behavioral pattern analysis relies on f_{c_α} and $\rho(\text{Psy}_d)$. As per the condition, f_{c_α} and Q outputs in either 1 or 0 require psychological qualities of data and behavior analysis can be successfully observed. The state changes based on equations (5) and (6) are presented in Figure 4.

The $\rho(\text{Beh}_p)$ is the input for the classification process as represented in Figure 4. For $\min\{\rho(\text{Beh}_p)\} \in t$, the classification for S_{ch} as in equation (4) is analyzed. Contrarily, if the $S_{ch} \neq \text{Beh}_{c_\alpha}$, then state 1 (min) to state 2 (max) process is transited. Therefore, (N, Ab, d) form a set of linear 2 classifications for which the association is performed. Contrarily, if f occurs as the failing condition $\forall S_{ch} \neq \text{Beh}_{c_\alpha}$ other

than Beh_p , then $f_{ob} \in t$ is segregated. This requires a new classification for reducing its impact. In this condition, if $S_{ch} = \text{Beh}_{c_\alpha}$, then swift interconnection and information sharing do not take place, and in the influencing factor of equation (1), it does not observe behavioral pattern for further process. This state processing model is performed through transfer learning depending on $Q = 1$ and $f_{ob} \forall ob \in t = f_a \forall a \in b$ to identify irregular behaviours and false rates in prediction, as well as influencing factors on college students at various time intervals t . The state changes of $0 < Q < 1$ are accurate for the data association based on the condition $S_{ch} = (\text{Beh}_t * \text{Beh}_{c_\alpha} / ob)$ that is observed and analyzed at different time intervals of $S_{ch}(t) = \text{Beh}_t(t - f_{ob}/f_a) + \text{Beh}_{c_\alpha}(t) \forall n \in t$ and $i \in B$, respectively. The false rate and irregular activities detection process through the acquired data association for analyzing false rate and process time in $(t - f_{ob}/f_a)$, and this is the state changes at t instance, where $f_{ob} \neq f_a$. At the initial state of Beh_t , $\rho(\text{Psy}_d)$ is computed through the state processing model $\text{Beh}_t(t - f_{ob}/f_a)$ based on Q . This state change is classified as normal and abnormal behaviors based on psychological data observation. This classification process is modeled using the f influencing factor as follows:

$$S_{ch} = Q * \left[\frac{\rho(\text{Psy}_d)}{[\text{Psy}_d - \text{Beh}_d]} \right]^{c_\alpha} * \left(t - \frac{f_{ob}}{f_a} \right). \quad (7)$$

Equation (7) represents the first outcome of the classification process and provides a solution of one as $Q = 1$ and $\text{Beh}_d = 0$, and $\text{Psy}_d = 1$. Therefore, it is considered as $S_{ch} = \sum_{ob \in b} (\text{Psy}_d)_{ob}$ or Psy_d until this condition $[1 < t - (f_{ob}/f_a) < t]$ is addressed. Therefore, the consecutive state changes in data association of Psy_d and Beh_d are analyzed and observed through a wireless network $(t - f_{ob}/f_a)$, where the probabilistic state processing model classification and appropriate changes are explained in a detailed manner.

3.2. State Model Classification Process. The previous psychological observation data of influencing factors Q and $\rho(\text{Psy}_d)$ are the associated normal and abnormal data in the state processing model based on the mobile wireless

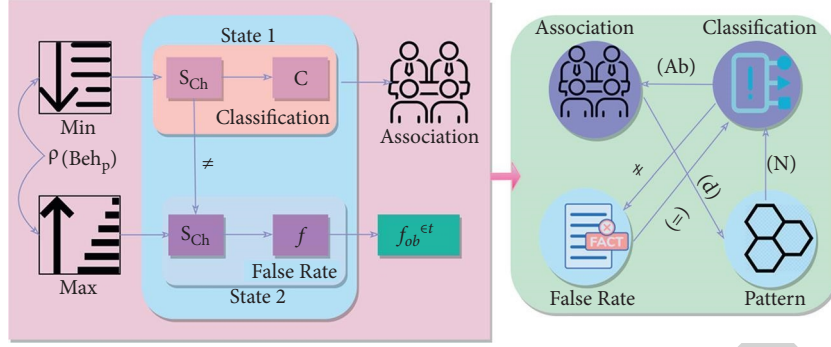


FIGURE 4: State changes for $t \in \text{Beh}$ and $C_\alpha \in \text{Beh}$.

network. In particular, the state changes and differing conditions of equation (1) are performed in the association with data to increase organization precision. The probability of Beh_d based on the state model classification process is competed as in

$$\rho(\text{Psy}_d) = \left(\frac{\rho(\text{Psy}_d \cup \text{Beh}_d)}{\rho(\text{Beh}_d)} \right). \quad (8)$$

The data association for state change classification using behavior-based psychological data observation relies on transfer learning. This classification is used to associate the data for both normal and abnormal instances. The above conditions are verified with the state processing instances using college student's behavior observation. The state change-based classification process depends on varying observations for analyzing the behavioral pattern detection and data association probabilities at any time instance of abnormal psychological data detection. Hence, the condition for abnormal psychological data observation is the same for all the college students, which follow the association procedure through the state model classification. The state model classification determines both the psychological and behavior data by estimating the Beh_d acquired information and association of data for given time intervals. The state changes based on classification $C(N, Ab)$ rely on a maximum deadline (t), and Psy_d is computed as follows:

$$C(N, Ab) = \left[\text{Beh}_d - \left(\frac{\text{Psy}_d}{f_{ob} - f_{c_a}} \right) \right] - Q + 1. \quad (9)$$

In this behavioral pattern observation and further state changes based on computing probability, the aim is to observe association throughout if the state changes remain the same; then, it is organized or else the new observation of data is identified as an influencing factor. The state changes are verified using observation at random time intervals. The output is a series of data associations that reduces the sequence of data associations, and therefore, the actual data extraction Psy_d is given as follows:

$$Q(\text{Psy}_d) = \max \left[\frac{\text{Beh}_d \times f_{ob}/f_a}{Q - \text{Beh}_{c_\alpha}(t) * f_{ob}/f_a} \right]. \quad (10)$$

In equation (10), the random observation intervals of data association (as per the state changes) are either Q or Psy_d , and in both instances, if the actual data extraction of $Q = 0$, then $Q = \text{Psy}_d = \text{Beh}_d$ which is the maximum positive psychological quality and if the abnormal data is observation outputs is zero whereas the normal data observation outputs in one. Therefore, the association of $\text{Beh}_d = \text{Psy}_d$ is a reliable solution where the processing time for all the psychological quality observations is analyzed in the above equation (1). This is acquired for all $ob \in t$ and $a \in b$ as in equation (1). The data association process in this observation is available in all Beh_d , where normal and abnormal data are observed, and hence, the series data extraction is ideal as in equation (1). The computation of $\rho(S_{ch})$ depends on the influencing factor based on equation (1). In any instance of Beh_d , if $\text{Psy}_d < \text{Beh}_d$, then abnormal observation occurs, which again results in data association. The classification for the data association process is illustrated in Figure 5.

The association between N and Ab is determined using S_{ch} classified (and also classified). This relies on the state transitions as presented in Figure 4. If the association fails, then $\{f_{ob}\} \in t$ is segregated for t or C_α classification. Therefore, this identification requires a state change for transferring $\rho(\text{Beh}_p)$ from min to max or vice versa (refer to Figure 5). Based on the association, the false rate and association (after classification) are presented in Figure 6.

The observation-based false rate and associations are improved after the classification process. In this process, the differences are suppressed for improving the classifications. Based on the state transitions, the learning process improves the processing. Therefore, the conditional verification as in Figure 4 is performed for recurrent and nonrecurrent associations. This improves the association count. As the association between the classified and identified data input increases, the false rate for an observed interval decreases (refer to Figure 6) compared to the one observed before classification. The day-to-day behavior observation and psychological disorders are identified and processed by college students for data association analysis; then, the false rate and irregular behavior and observation are perceived using state model processing, and these additional processes prevent the influencing factors and reduce the processing time. If the condition $\rho(\text{Psy}_d) > \rho(\text{Beh}_d)$, then abnormal behavior detection as in equation (8) is responsible for

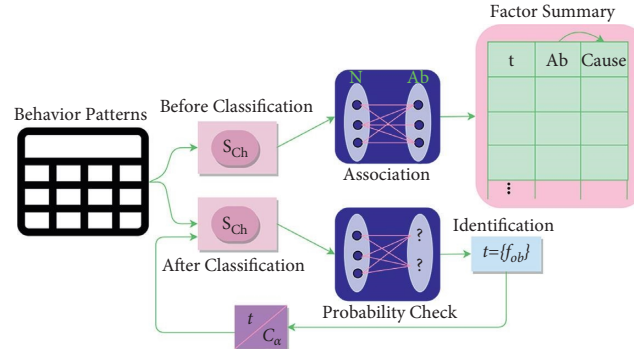


FIGURE 5: Classification for data association.

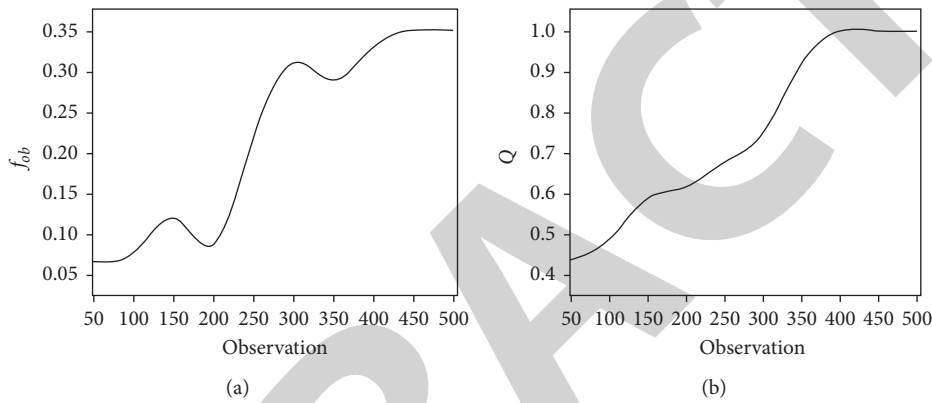


FIGURE 6: False rate and association for different observations (after classification).

changing the states based on f . The state change is validated for available data observation through b in the wireless network other than $(t - f_{ob}/f_a)$. This consecutive manner helps to reduce the processing time in data association of remaining Psy_d to maximize S_{Ch} .

Therefore, the state processing is based on C_α other than f , the random time interval of $[1, C_\alpha]$ helps to detect the abnormal behavior of $t\text{VPsy}_d$ and is to improve the prediction accuracy of psychological data observation of college students based on the $0 < Q < 1$ condition for any b with different organizations. The proposed method observes $\rho(\text{Beh}_d) > \rho(\text{Psy}_d)$ until state changes remain the same that is estimated, where the different b is provided based on the behavior-based psychological data of association. In this manuscript, if the positive psychological quality and behavior increase, and therefore, the minimum false rates are attuned, and hence, the behavior or habitual features of young people’s observation increase through transfer learning, it identifies the irregular behaviors and abnormal activities of college students in that wireless network. The abnormal behavior detection validates the state changes based on the classification process and influencing factors. This prediction and influencing factors in big data on college students under wireless networks are used to reduce the false rate and processing time.

4. Discussion

The proposed method is validated using experimental analysis using the dataset [29]. This dataset provides emotional data for identifying the psychological behavior of 19 human subjects. From the total of 64 subjects, human aging between 14 and 20 years old are filtered and 18 emotional choices are utilized for detecting the behavior pattern. The data include 11 fields for identifying the emotion using situational phrases. With these data, the metric accuracy, precision, false rate, and processing time are comparatively analyzed by varying the observations and classifications. In this comparative analysis, EAM-Bi-LSTM [16], EDM-DL [17], and MA-RP [25] methods are compared with proposed BPRM method.

4.1. Accuracy. In Figure 7, the different day-to-day behavior of college students and their associated psychological data is observed for determining the influencing factors for organizing the quality of observation. The influencing factor information is aided for analysis in treatment, recommendation, and diagnosis of psychological disorders, etc, which are used to improve the prediction accuracy through conventional wireless networks. It does not provide interconnection and information sharing relies on the data

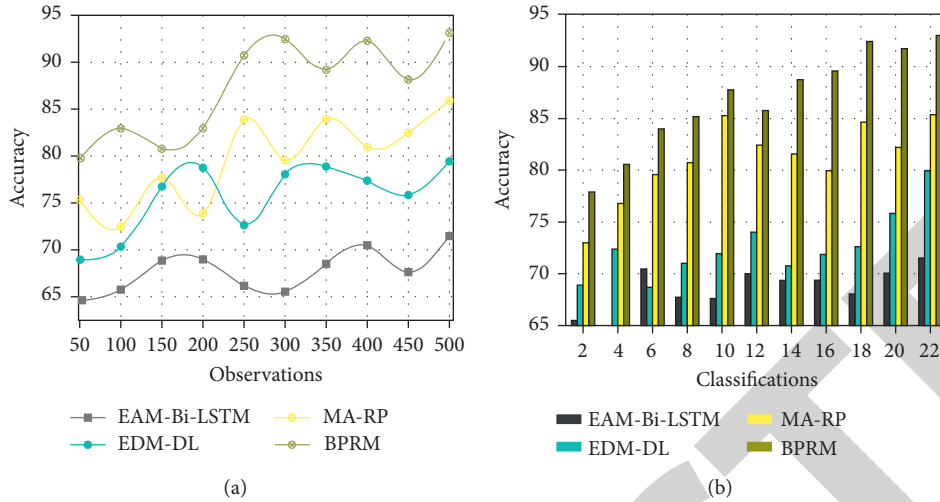


FIGURE 7: Accuracy analysis.

association based on the state processing model at random time intervals. The detection of irregular behaviors and false rate observations is classified based on the state changes from the first-stage outputs in psychological data observation that enhance the accuracy and organization precision for the behavior analysis, wherein the acquired information based on the data association through the transfer learning can be used for detecting irregular behaviors and responses. This issue is addressed using whether the new data are identified as an influencing factor that can be analyzed for observing the successive state processing models based on the learning process depending on the false rates, preventing irregular behaviors. Therefore, the learning process classifiers based on the state changes in both normal and abnormal data observations are detected, preventing high prediction accuracy until new data are observed.

4.2. Precision. This proposed method for associating quality identification and abnormal data detection process achieves high precision and swift interconnection that depend on psychological big data and previous observations based on behavior or habitual features of people that rely on the actual data extractions at random time intervals that are used for detecting the abnormal data or irregular behavior or response prediction (refer to Figure 8). The consecutive process of psychological data observation and different behavior analysis based on normal data observation is associated, and the state changes are classified for observing the abnormal behavior based on psychological data through wireless networks due to different data associations. The psychological big data identification is based on the normal data observation using the acquired and organized information verification based on computation through transfer learning in the given time intervals for classifying the state processing model in identifying irregular behaviors for reducing the negative psychological predictions based on the quality of data that enhance the precision and accuracy in the behavior analysis of college students during abnormal

data detection. Therefore, the learning process based on normal and abnormal data observation estimation depends on other factors in the influencing factors based on behavior analysis, and therefore, the precision is high and diagnosis of psychological disorders also increases.

4.3. False Rate. The state processing and the behavior-based psychological data and observation are varied and are classified as normal and abnormal data based on the data association throughout the state changes that remain the same depending on the swift interconnection and information sharing using random observation intervals as represented in Figure 9. In this different behavior analysis of college students, for organizing the quality of observation based on time instances, such that $1 - ((\text{Psy}_d)_b / \prod (\text{Psy}_d + \text{Beh}_d)_a)$, the data association occurs due to improving prediction accuracy in the learning process. The behavior analysis based on acquired information of different data associations, the false rate, and irregular behaviors is detected in both classification process, and the association is observed as information for the series data association, wherein the different behavior analysis with the precise data observation based on the state remains same. In this proposed data association, the quality of observation is mitigated by detecting false rates through transfer learning based on both normal and abnormal data that are analyzed for further association and are considered for providing behavior-based psychological data for college students/young people. Therefore, the false rate is less compared to the other factors in behavior analysis based on psychological data prediction, and the false rate is detected.

4.4. Processing Time. The different psychological data observation through interconnection and information sharing analysis for false rate detection is represented in Figure 10. The proposed method achieves less processing time for determining the influencing factor by evaluating $\sum_{ob \in b} (\text{Psy}_d)_{ob} = \text{Psy}_d$ and f_{c_α} . In the different psychological

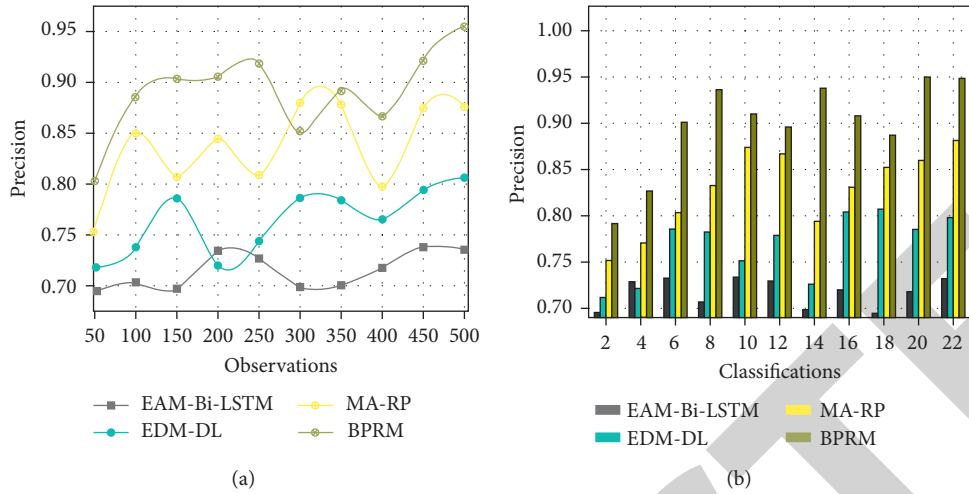


FIGURE 8: Precision analysis.

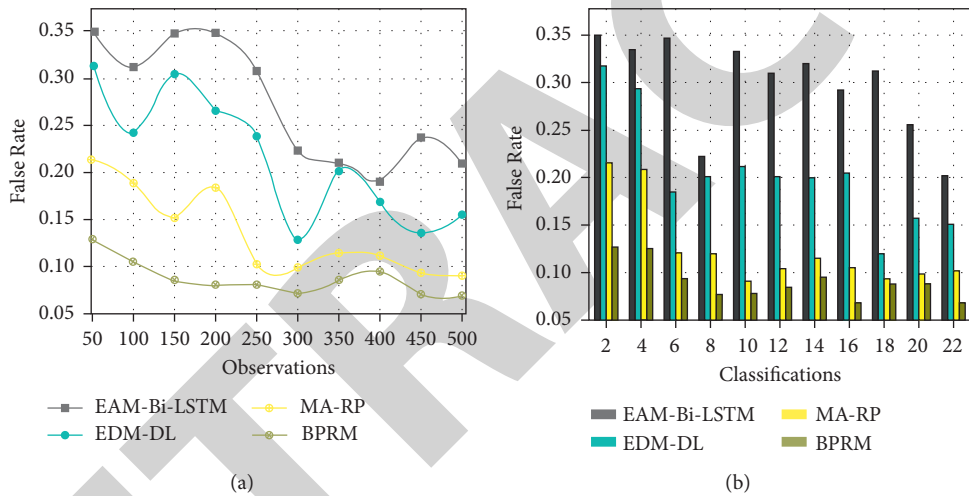


FIGURE 9: False rate analysis.

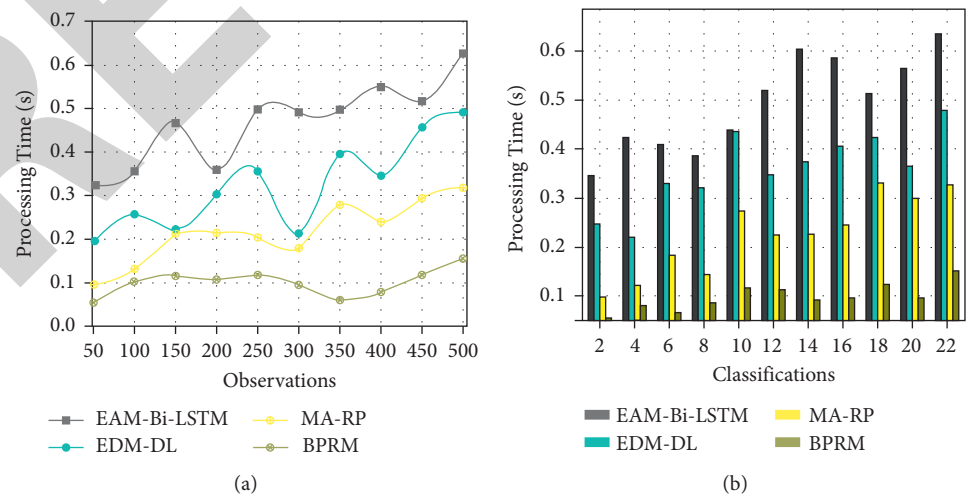


FIGURE 10: Processing time analysis.

TABLE 1: Comparative analysis (observations).

Metrics	EAM-Bi-LSTM	EDM-DL	MA-RP	BPRM
Accuracy	71.47	79.43	85.87	93.064
Precision	0.736	0.806	0.879	0.9557
False rate	0.209	0.155	0.091	0.0689
Processing time (s)	0.628	0.492	0.319	0.1544

Inference: the proposed method improves accuracy and precision by 14.14% and 14.87%, respectively. It reduces false rate and processing time by 8.28% and 11.3%, respectively.

TABLE 2: Comparative analysis (classifications).

Metrics	EAM-Bi-LSTM	EDM-DL	MA-RP	BPRM
Accuracy	71.51	79.98	85.34	92.978
Precision	0.732	0.798	0.881	0.9486
False rate	0.203	0.151	0.102	0.0688
Processing time (s)	0.635	0.477	0.327	0.1512

Inference: for the varying classifications, the proposed method improves accuracy and precision by 14.03% and 14.49%, respectively. It reduces false rate and processing time by 8.32% and 11.41%, respectively.

data observation, for analysis in treatment, recommendation and depression are analyzed based on transfer learning that relies on the series data association for classifying normal and abnormal data detection, and this sequential processes of behavior data are observed based on the condition of data association at the random observation interval, wherein the different state changes based on new data are identified using equation (7) computation. In this mobile wireless network, the psychological data of college students and behavior analysis are computed based on processing timeless observation and information sharing. The irregular behavior and responses detected depend on the normal and abnormal data observation that is the consideration of series data associations based on influencing factor (as in equation (9)). Based on the college student behavior analysis, the processing time is computed for influencing factor analysis.

4.5. Inference in Comparative Analysis. The comparative analysis presented in the previous section is tabulated for observations and classifications using Tables 1 and 2, respectively. The inference for these tables is presented with the percentage variation.

5. Conclusions

Psychological data analysis aids to identify the emotion and behavior of young people and the factors related to it. Identifying the influencing factor requires emotion and behavior data analysis observed in different situations. Therefore, this article proposed and discussed a behavioral pattern recognition method for identifying the impacting factors. This method is based on data association to maximize detection accuracy. Transfer learning-aided wireless data analysis is used for improving the precision by assigning different states. The states are based on behavior patterns

observed under different classifications. In the classification process, the probability-based data and emotion association, and false rate impact are considered. Based on this consideration, the state changes are performed for confining the false rate impact over the varying observation sequences. Therefore, the proposed method improves accuracy and precision by 14.14% and 14.87%, respectively. It reduces false rate and processing time by 8.28% and 11.3%, respectively, for the varying observations.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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