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Research Article

Wearable Psychological Stress Monitoring Equipment and Data Analysis Based on a Wireless Sensor

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With the rapid development of social economy, human psychological pressure is an important factor affecting human health. Excessive psychological pressure will lead to serious psychological diseases such as depression and anxiety. The traditional psychological stress monitoring method is mainly limited to the psychological scale. This method has a certain subjectivity, so its corresponding test data is not representative. At the hardware design level, this paper will select miniaturized, low-power, and low-cost microphysiological sensors to monitor the psychological pressure level discrimination indicators such as heart rate, body temperature, and heart rate waveform and fully optimize the layout of wireless sensors at the hardware layout level to achieve the high efficiency of the whole system. The detection of human pulse signal and heart rate signal is mainly carried out through microsensors, and the temperature signal is filtered and amplified, and analog-to-digital conversion is carried out to realize the accurate measurement of key signal waveform. At the level of hardware system and software algorithm, this paper creatively proposes a psychological stress recognition algorithm based on evidence theory. By extracting the collected key signal features, we can identify the primary stage of psychological stress and finally realize the evaluation and analysis of individual psychological stress through evidence theory. The experimental results show that the trust degree of an individual psychological stress test is improved by 0.187 compared with the traditional algorithm, and the corresponding psychological stress trust degree is up to 0.988, which has obvious advantages.

1. Introduction

As an important factor affecting human mental health in modern society, the monitoring and data analysis of its key indicators have attracted more and more attention of research institutions and researchers. The traditional psychological stress monitoring is mainly a psychological scale. The commonly used psychological stress scale mainly includes a perceived stress scale, psychological stress scale, and related stress scale. It needs human subjective intervention in identifying and analyzing the level of human psychological stress. Therefore, the corresponding discrimination results often have serious subjective performance, which cannot represent the real situation of individual psychological pressure in a certain sense [1–3]. At the level of traditional psychological stress observation factors, it mainly involves human physiological measurement and physical means measurement. At the level of corresponding physiological measurement, it mainly needs the help of some external instruments and equipment to obtain by sampling and analyzing the corresponding physiological data of the human body. Based on this, the traditional evaluation indexes of human psychological stress include ECG, heart rate, human temperature and photoelectric pulse, speech, and EEG signals [4, 5]. Based on the above relevant indicators, the traditional psychological stress assessment methods include an interview method, psychological detection method, and questionnaire method, but such assessment algorithms often require the active response and cooperation of participants to achieve a more ideal assessment state.

Therefore, the traditional psychological stress monitoring and assessment algorithms have serious subjectivity and lose some authenticity [6–8]. Therefore, how to monitor and analyze human physiological data in real time through sensors, so as to objectively and accurately analyze and study individual psychological pressure and realize the objective quantitative evaluation of individual psychological pressure, is the focus of this study.

Microphysiological sensor network technology with the continuous development of artificial intelligence and pattern recognition technology and low-power, miniaturized, and high-precision wireless physiological sensors provide the possibility for real-time monitoring of key evaluation indicators of psychological stress [9, 10]. The wearable intelligent device formed by miniaturized sensors greatly reduces the cost of real-time monitoring of human physiological characteristics, and its corresponding wearable device operation tends to be simpler and simpler [11]. Through the real-time monitoring of a heart rate sensor, temperature sensor, blood pressure sensor, and acceleration sensor integrated on wearable intelligent devices, individual physiological data can be accurately obtained [12, 13]. The emergence of a microwireless physiological sensor network further reduces the difficulty of data processing. It can realize the real-time transmission of the corresponding physiological data of the human body to the base station or data processing center in a cooperative manner, so as to realize the accurate evaluation and real-time tracking analysis of individual psychological stress. At the same time, individuals can also adjust and treat themselves through real-time data, so as to timely alleviate their own psychological pressure [14].

Based on the above psychological stress detection situation, this paper will design a wearable psychological stress monitoring and data analysis system based on low-power small physiological wireless sensors and conduct detailed research from the software and hardware levels. In terms of system hardware, this paper will select miniaturized, low-power microphysiological sensors to monitor human heart rate, temperature, heart rate waveform, and other psychological stress level discrimination indicators and comprehensively optimize the layout of wireless sensors to achieve high efficiency, high system transmission rate, and anti-interference performance; the sensor data acquisition module collects the human pulse signal and heart rate signal, filters and amplifies the temperature signal, and performs analog-to-digital conversion to achieve accurate measurement of key signals; at the system software level, this paper innovatively proposes a system based on a psychological stress recognition algorithm based on multiphysiological parameter fusion decision-making based on evidence theory. Compared with the traditional algorithm, the algorithm can perform comprehensive judgment and analysis based on more key signals, thereby improving the accuracy and reliability of the judgment and analysis. In this algorithm, multiple physiological data indicators need to be collected and quantified by extracting the key signal features collected, identifying the primary stage of psychological stress, and finally realizing the evaluation and analysis of individual psychological stress through evidence theory. The experimental results show that the trust degree of the individual psychological stress test is 0.187 higher than that of the traditional algorithm, and the corresponding psychological stress trust degree is as high as 0.988, with obvious advantages.

Based on this, the main contents of the article are arranged as follows: the second section of the article will focus on the current research status of wearable psychological stress monitoring devices based on wireless sensors. The third section will focus on the analysis and research of the psychological stress recognition algorithm based on the fusion decision of multiple physiological parameters based on evidence theory and design the software and hardware of wearable psychological stress monitoring equipment. In the fourth section of this paper, the wearable devices designed in this paper will be tested and verified, and the data analysis will be given. Finally, this paper will be summarized.

2. Correlation Analysis: Research Status of Wearable Psychological Stress Monitoring Equipment and Data Analysis Based on a Wireless Sensor

At the level of psychological stress monitoring and data analysis, a large number of scientific research institutions and researchers have analyzed from different angles and also designed a large number of individual psychological stress assessment systems. At the level of corresponding indicators for evaluating the level of psychological stress, relevant researchers in the United States have analyzed and studied individual EEG signals, which mainly study the correlation between EEG asymmetry and psychological stress and depression level. The corresponding experimental results show that EEG asymmetry can indeed be used as an important indicator of individual psychological stress; however, it is relatively difficult to monitor EEG signals [15]. Relevant scientific research institutions in Japan have focused on the correlation between individual psychological stress and individual voice expression and workload. The corresponding fundamental frequency and fundamental frequency jitter of voice signal can best reflect the current pressure faced by individuals. At the same time, with the increase in workload, the corresponding fundamental frequency jitter is more severe [16]. At the level of psychological stress assessment, the mainstream research focuses on human intervention and physiological parameter monitoring. At the level of corresponding physiological parameter monitoring, the mainstream research includes physiological parameter monitoring technology, psychological stress inducing factor setting, and individual psychological stress assessment algorithm. Relevant researchers in the United States have established physiological stress identification models based on four different stressors. At the same time, the stability and reliability of the model are verified [6, 17, 18]. Relevant European institutions assess human psychological stress based on ECG, skin surface temperature, skin surface impedance, and other parameters monitored by individuals,

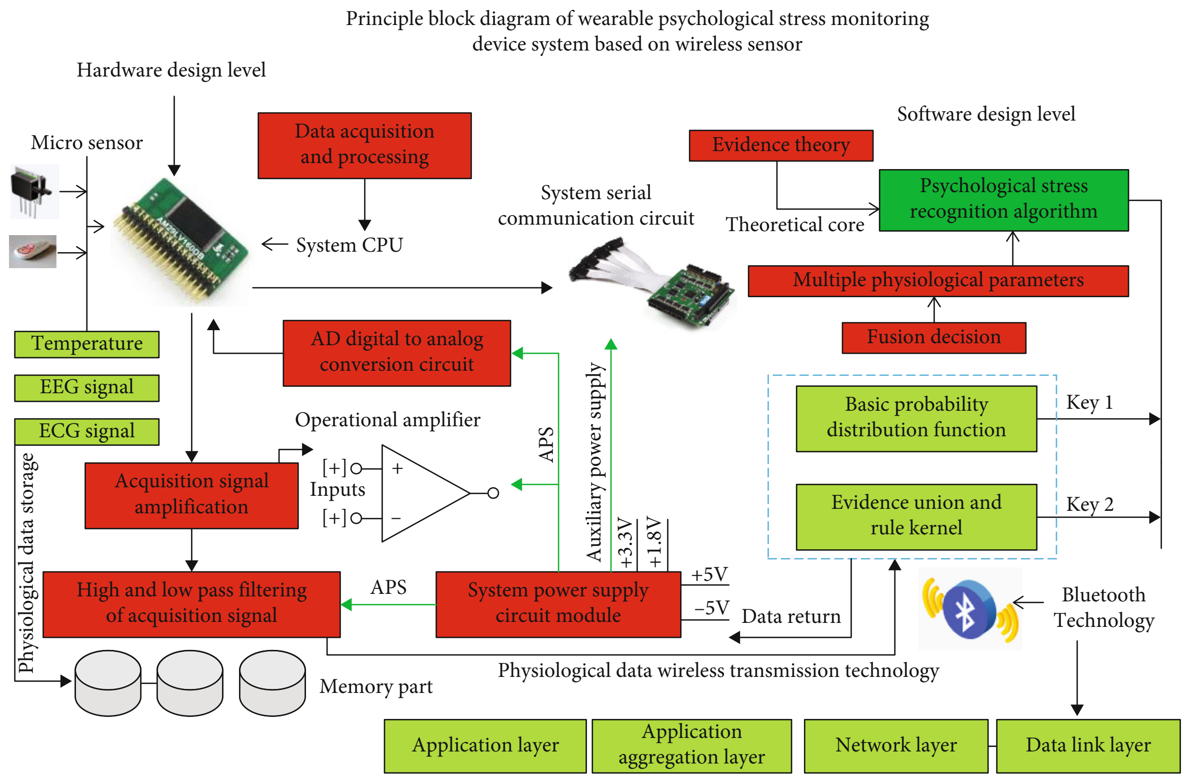

FIGURE 1: Principle block diagram of the wearable psychological stress monitoring device system based on a wireless sensor.

and the corresponding reliability of psychological stress assessment is about 90%, but this method relies too much on participants' subjective emotional memory ability. At the same time, the response time of EEG signal to psychological stress and the initial emotional representation time are uncertain, so the reliability of the result is low [19, 20]. Relevant American research institutions have proposed a plethysmogram technology to evaluate individual psychological stress. It mainly obtains the plethysmogram of individual heart under static and pressure conditions and then evaluates individual stress by analyzing image features [21, 22]. The advantage of this method is that it does not require individual contact with relevant sensors. However, the reliability of psychological stress corresponding to this method is low [23, 24].

3. Research on Wearable Psychological Stress Monitoring Equipment and Data Analysis Based on a Wireless Sensor

This section mainly analyzes and studies the software and hardware design of the wearable psychological stress monitoring system based on a microwireless sensor network. The corresponding system design principle block diagram is shown in Figure 1. It can be seen from the figure that at the hardware design level, this paper selects the physiological signal acquisition circuit with a single-chip microcomputer as the core, in which the corresponding core module includes a signal acquisition circuit, signal amplification circuit, signal filter circuit, digital-to-analog conversion circuit, serial communication circuit, and power supply circuit. The core algorithm at the corresponding software architecture level is mainly the psychological stress identification algorithm based on evidence theory and multiphysiological parameter fusion decision. The algorithm mainly realizes the evaluation and analysis of individual stress based on the elements collected by the sensor. The main purpose of the algorithm is to establish the psychological stress evaluation and identification model. The core elements include the basic probability distribution function kernel and the evidence association and rule kernel.

3.1. Analysis and Research on the Psychological Stress Recognition Algorithm Based on Evidence Theory and Multiphysiological Parameter Fusion Decision. In order to solve the evaluation accuracy and objectivity of an individual psychological stress evaluation algorithm, a psychological stress recognition algorithm based on evidence theory and multiphysiological parameter fusion decision-making is constructed in this paper. A variety of physiological information such as ECG, skin temperature, and EEG are collected by wireless sensors, and the three kinds of information are combined to form an information fusion body. Before the physiological information fusion, each physiological information acquisition sensor needs to preprocess and analyze the corresponding data and extract its corresponding features; then, the corresponding preprocessing results are evaluated and calculated through the multievidence theory, so as to obtain the probability value of the recognition target corresponding to each physiological parameter compared with other sensors. Finally, the final

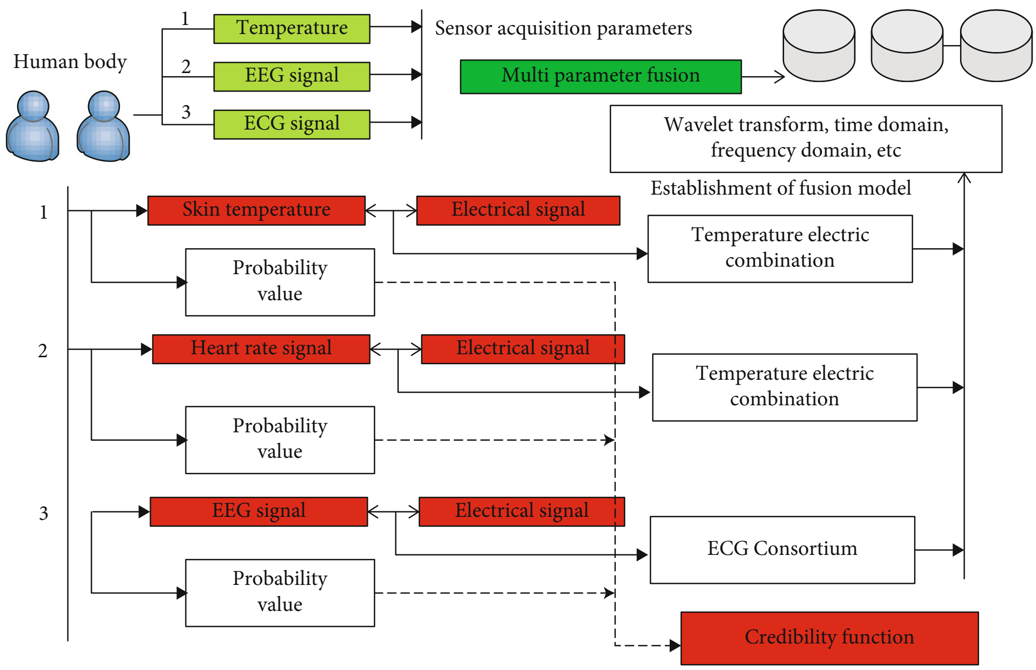

FIGURE 2: Operation block diagram of the psychological stress recognition algorithm based on evidence theory and multiphysiological parameter fusion decision.

evaluation result is obtained through the psychological pressure credibility function given by the fusion model. The operation block diagram of the psychological stress recognition algorithm based on evidence theory and multiphysiological parameter fusion decision-making proposed in this paper is shown in Figure 2.

It can be seen from the figure that the main core of the algorithm proposed in this paper is two parts, corresponding to the analysis of basic probability distribution function of sensor physiological characteristics, model evidence fusion, and standard definition.

The basic probability distribution function of sensor physiological characteristics is the basis of evidence theory. Combined with the psychological stress characteristics, the target of physiological characteristics to be detected is set as q, and the corresponding b is set as the judgment process of sensor local feature analysis. Therefore, it can be concluded that the representation framework of individual psychological stress recognition corresponds to [d1, d2, d3, d4], and the corresponding d1 represents individual psychological stress. The corresponding d2 represents that the individual does not have psychological stress, d3 represents that the individual does not have any state, and the corresponding d4 represents that the two states of the individual exist at the same time. In the setting of this paper, it is assumed that d3 does not exist, and the combination of d3 and d4 into an individual psychological stress state is not clear. According to the evidence theory, based on this, a specific sensor needs to be assigned probability in an identification space, and the corresponding probability function needs to meet formula (1), where the corresponding c represents the identification space and the corresponding $w : 2^{c-[0,1]}$ represents the basic probability assignment according to the specific algorithm.

$$0 < w(c) < 1 \longrightarrow w(\partial) \longrightarrow w(c1) + w(c2) + \cdots w(c_n) = 1. \tag{1}$$

Based on formula (1), the formula corresponding to the trust function of the specific physiological sensor and its corresponding basic probability assignment relationship is shown in formula (2). A in the corresponding formula (2) represents the specific monitoring physiological index in the sensor and the identification target in the evidence theory:

$$w(b1) + w(b2) + w(b3) + \cdots w(bn) = \mathrm{Bel}(b). \tag{2}$$

Based on formula (2), the calculation formula of a likelihood function of target recognized by a specific sensor is further deduced. The corresponding likelihood function is shown in

$$P(b) = 1 - \left[w\left(\overline{b1}\right) + w\left(\overline{b2}\right) + w\left(\overline{b3}\right) + \cdots w\left(\overline{bn}\right) \right]. \tag{3}$$

Based on this, the uncertainty of psychological stress assessment conveyed by the physiological characteristics monitored by specific sensors is mainly composed of formulas (1) and (2), and the corresponding uncertainty function calculation formula is shown in

$$\begin{cases} \mathrm{error}_1 = P(b_1) - \mathrm{Bel}(b_1), \\ \mathrm{error}_2 = P(b_{\dots}) - \mathrm{Bel}(b_{\dots}), \\ \mathrm{error}_3 = P(b_n) - \mathrm{Bel}(b_n). \end{cases} \tag{4}$$

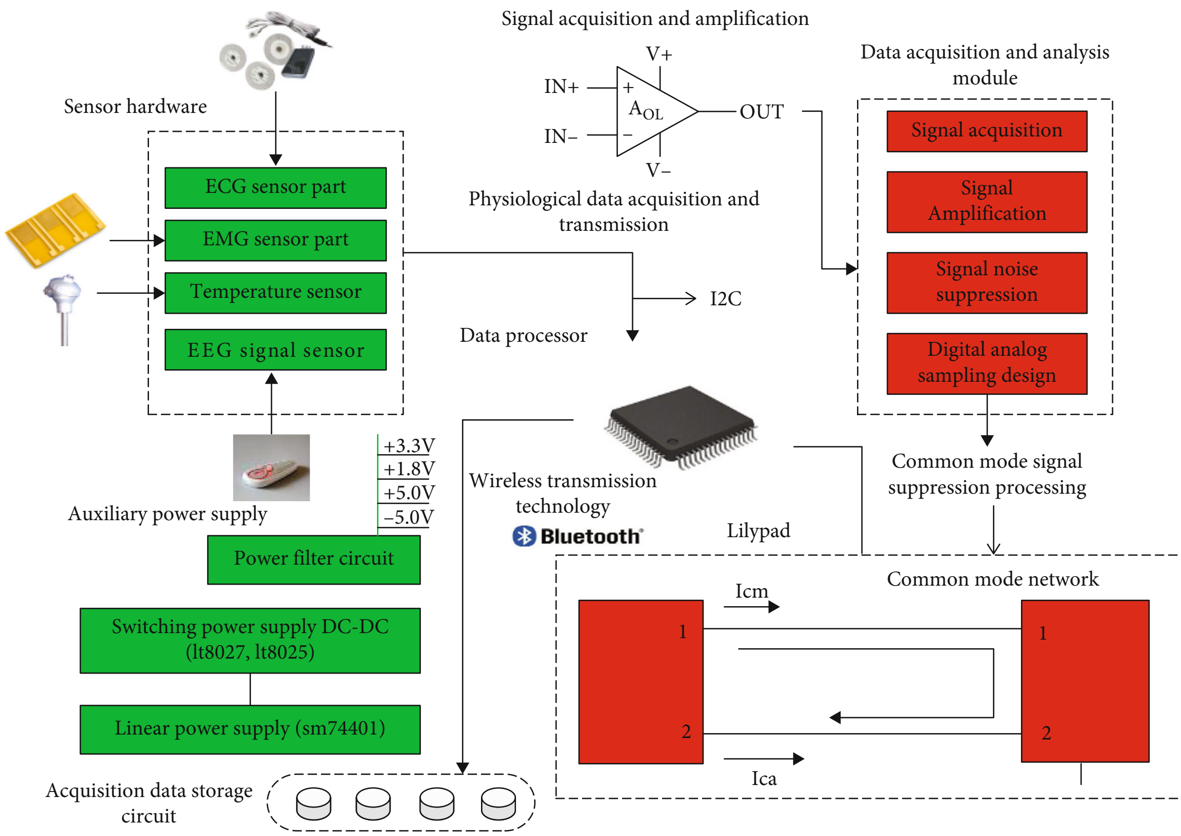

Figure 3: Hardware principle block diagram of wearable psychological stress monitoring based on a wireless sensor.

Combining formulas (1)–(4) can basically determine the basic probability distribution function of sensor physiological characteristics.

At the level of model evidence fusion and standard definition, it is mainly discussed that multiple physiological features are combined and analyzed according to certain laws, so as to realize the multiparameter fusion of psychological stress assessment. The corresponding fusion function is shown in formula (5). The corresponding k in the formula represents the degree of conflict after the judgment of physiological features among multiple sensors, and the closer the corresponding value is to 1, the more intense the conflict between the preliminary judgment results corresponding to the sensor. When the corresponding value is greater than or equal to 1, it is determined that the judgment result is completely excluded. The calculation formula of the corresponding conflict coefficient k is shown in formula (6).

$$\text{error}(b) = \frac{[(\text{error}_1(x_1) * \text{error}_2(x_1)) + \cdots + (\text{error}_i(x_i) * \text{error}_i(x_i))]}{1-k}, \tag{5}$$

$$k = 1 - [[(\text{error}_1(x_1) * \text{error}_2(y_1)) + \cdots + (\text{error}_i(x_i) * \text{error}_i(y_i))] \longrightarrow x_i \cap y_i. \tag{6}$$

For the preliminary identification results of multiple sensors, it needs to meet a certain exchange law and combination law. The corresponding satisfaction formula is shown in formula (7). The corresponding x, y, and z in the formula represent the physiological characteristics monitored by specific sensors, that is, the evidence body in evidence theory.

$$x \otimes y \otimes z \longrightarrow y \otimes x \otimes z \longrightarrow y \otimes z \otimes x. \tag{7}$$

Based on the above theory, the final evaluation principle of psychological stress is as follows, which is also the conclusion of this algorithm:

(1) The trust function value corresponding to the psychological stress of the final decision is the largest among all the sensor trust function values

(2) The value of the trust function corresponding to the final evaluation of psychological stress is greater than 1/2, and the trust function under the fusion is more than twice the value of the trust function of each specific sensor

3.2. Design and Research of a Wearable Psychological Stress Monitoring Device Based on a Wireless Sensor. At the hardware level, this paper designs a wearable psychological stress monitoring system based on the above data processing algorithm. The system mainly monitors individual heart rate, EEG signal, skin temperature, and heart rate waveform based on microphysiological sensors. The corresponding hardware system mainly includes various physiological sensors, power supply module, data acquisition module, data

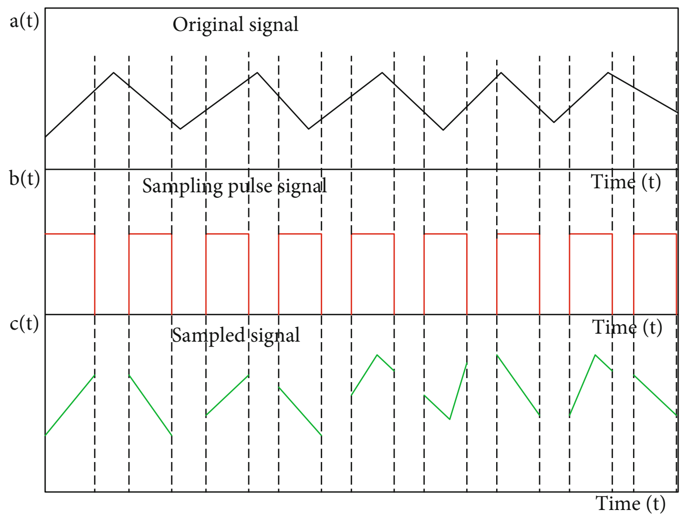

FIGURE 4: Waveform diagram of digital-to-analog acquisition conversion form of the wearable psychological stress monitoring system based on a wireless sensor.

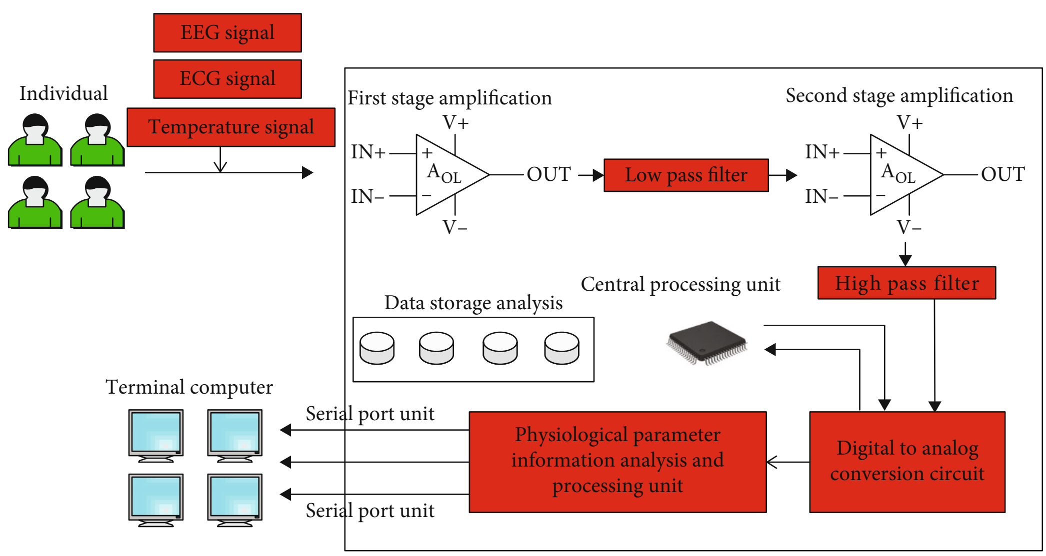

FIGURE 5: Hardware circuit principle block diagram of the data acquisition and analysis module.

analysis module, and wireless transmission module. The core module includes data acquisition module, data analysis module, and wireless transmission module. Figure 3 is the hardware block diagram of the system. It can be seen from the figure that the hardware system mainly focuses on the design of physiological data information acquisition circuit, and its key indicators include signal acquisition and amplification factor, signal noise and interference suppression processing, digital-to-analog sampling, and conversion rate design.

The central processor part of the system, that is, the signal data processor part, mainly selects STM32 as the core data processor, which can receive the data corresponding to the data acquisition chip using the I2C interface and transmit the data based on the I2C transmission mode. At the same time, the processor selected in this paper also has the function of connecting with the wireless sensor network. Based on this, the single-chip microcomputer model selected in this paper is LilyPad, which has obvious interface and volume advantages as a wearable intelligent device.

In the corresponding data acquisition and analysis module, we need to focus on signal acquisition and amplification, signal noise and interference suppression processing, digital-to-analog sampling, and conversion rate design. In the corresponding signal amplification part, this paper fully combines the weak characteristics of ECG and EEG signals to design the corresponding amplification factor (300 times in this paper) to meet the size of subsequent voltage window and corresponding analysis requirements. At the corresponding noise and interference suppression level, it mainly prints common mode signals mixed in ECG and EEG signals, power frequency power supply clutter signals, and

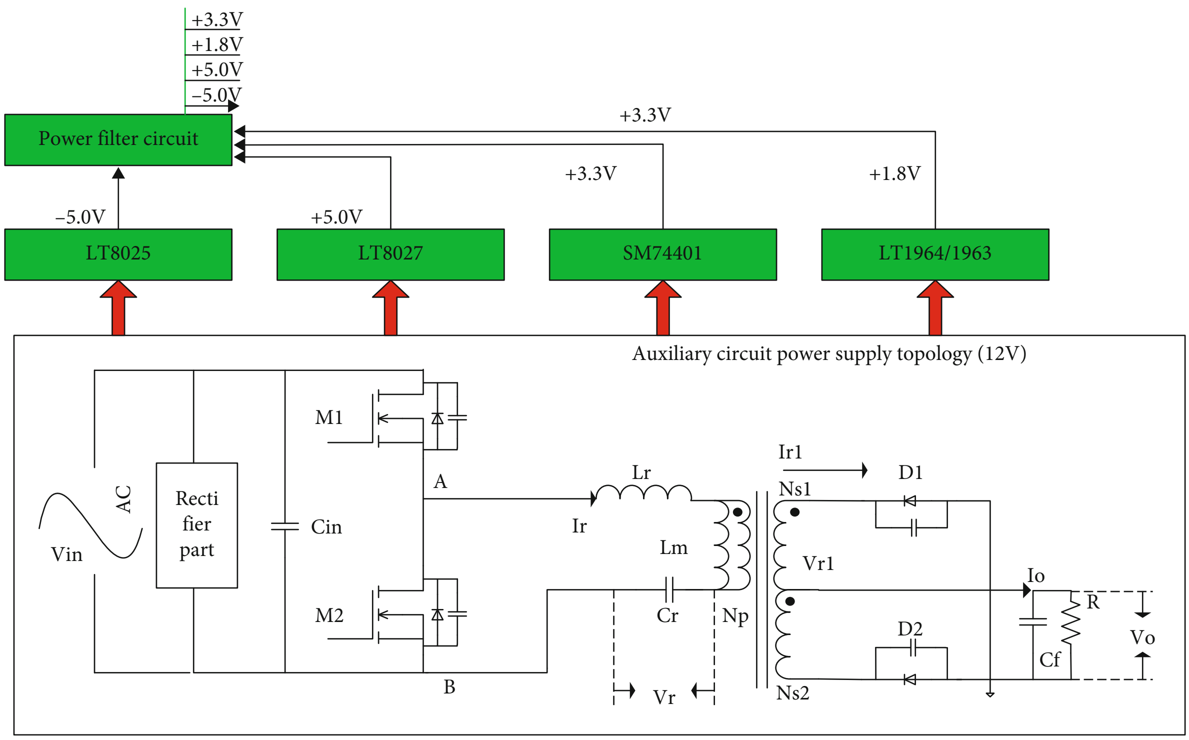

Figure 6: Schematic diagram of the auxiliary power circuit of the hardware system of the data acquisition and analysis module.

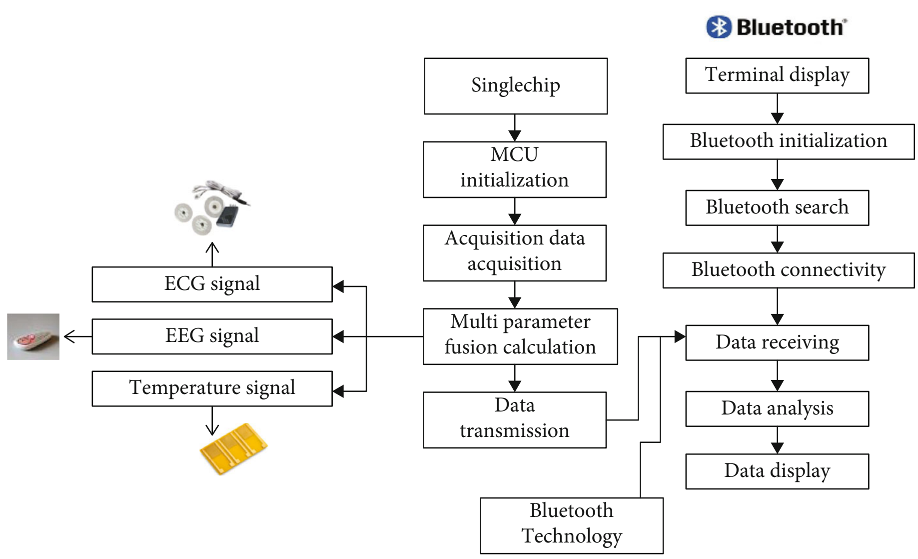

Figure 7: Schematic diagram of hardware system software algorithm flow architecture of the data acquisition and analysis module.

certain interference signals. At the level of corresponding digital-to-analog conversion and sampling rate, the sampling accuracy needs to be considered. The form of digital-to-analog conversion signal used in collecting ECG, EEG, and skin temperature in this paper is shown in Figure 4. In the corresponding figure, $a(t)$ represents the original signal, $b(t)$ represents the sampled pulse signal, and $c(t)$ represents the sampled signal. It can be seen from the formula that the sampling accuracy is mainly determined by the resolution of the sampling chip.

The hardware circuit of data acquisition and analysis module mainly includes front-end circuit module (including front-end amplification module, high-pass filter part, rear-end amplification part, and low-pass filter part), analog-to-digital conversion part, auxiliary power supply part, serial port circuit module part, etc. The corresponding hardware circuit transmission mode of each part is shown in Figure 5. It can be seen from Figure 5 that the precircuit module needs a total of 40 amplifiers. At the same time, the amplification factor of the prestage amplification circuit

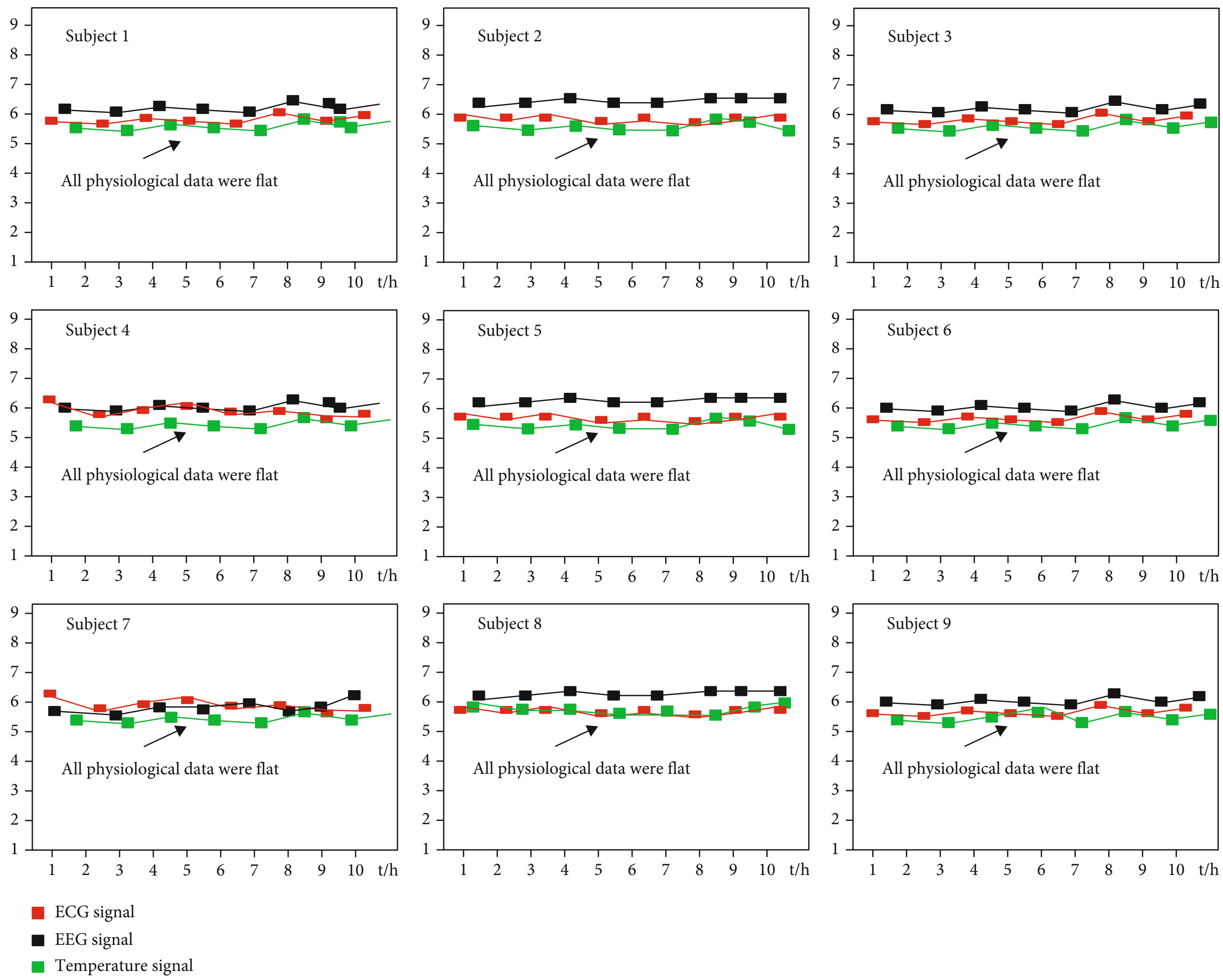

Figure 8: ECG signal, EEG signal, and skin temperature sampling waveform in a calm period.

designed in this paper is 7 times, and the voltage amplitude collected by the corresponding original circuit is 1 mv; then, the signal amplitude amplified by the amplification circuit is 7 mv. At the corresponding differential mode signal elimination level, the differential circuit is mainly used to eliminate the corresponding interference signal. Based on this, the magnification calculation formula of the primary amplification circuit can be obtained, as shown in formula (8). The corresponding resistance in the formula is the amplification factor matching resistance.

$$G = \frac{R_1 + R_0}{R_0}. \tag{8}$$

Based on the above primary amplification, filter processing is carried out, and enter the secondary amplification part at the same time. The magnification selected in the corresponding secondary amplification part is 8 times. At this time, the calculation formula of the corresponding system signal magnification is shown in formula (9), and the corresponding magnification is 56 times.

$$G_{\text{all}} = \left[G_1 : \left(\frac{1 + R_1}{R_0}\right)\right] * \left[G_2 : \left(\frac{1 + R_2}{R_0}\right)\right]. \tag{9}$$

The high-pass filter used in this paper is RC structure, which mainly uses the resonance of resistance and capacitance to filter the high-frequency signal. At the same time, the circuit design of this high-pass filter is simple and the cost is low. Based on equations (10) and (11), the filtering time constant and the corresponding minimum frequency of the high-pass filter used in this paper can be calculated.

$$\begin{cases} f_1 = \dfrac{1}{(2 * \pi * R_1 * C_1)}, \\ f_2 = \dfrac{1}{(2 * \pi * R_2 * C_2)}, \end{cases} \tag{10}$$

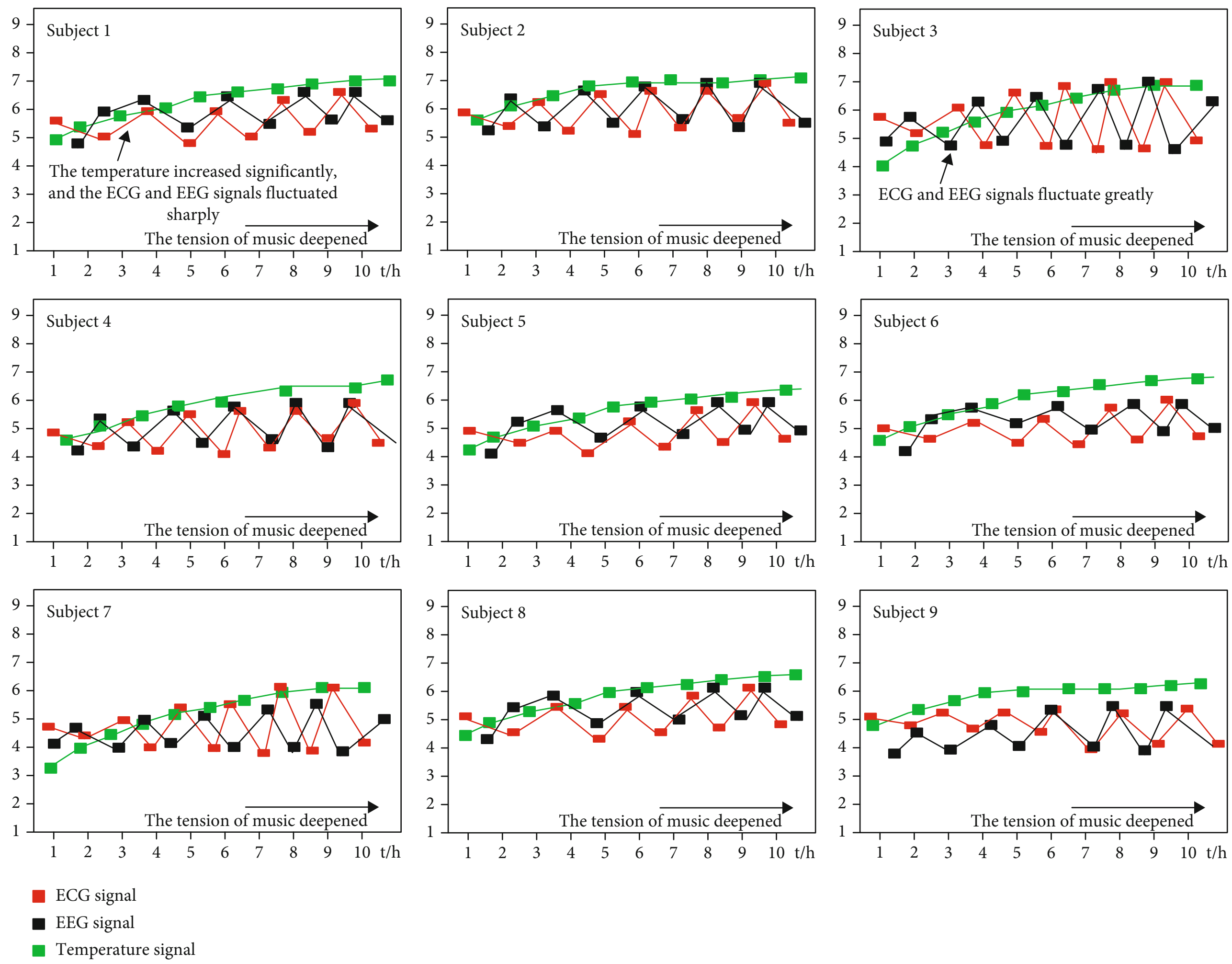

Figure 9: ECG, EEG, and skin temperature sampling waveforms of experimental participants in the psychological stress simulation period.

$$\begin{cases} t_1 = R_1 * C_1, \\ t_2 = R_2 * C_2, \\ t = t_1 + t_2. \end{cases} \tag{11}$$

In the corresponding auxiliary power supply circuit, the conventional DC-DC power chip is mainly used to set up the corresponding auxiliary circuit. The main level of the system designed in this paper includes conventional voltages such as 3.3 V, 5 V, 1.8 V, and -5 V. The chips mainly selected in this paper include power chips such as LT8025, LT8027, and SM74401. The schematic diagram of the corresponding auxiliary power supply circuit is shown in Figure 6.

At the level of corresponding wireless transmission module circuit design, this paper mainly selects Bluetooth technology to realize the circuit design of the wireless transmission module. The corresponding Bluetooth module selected in this paper is HC-09, its corresponding transmission rate can reach 1 Mbps, and the corresponding maximum transmission distance is about 100 m. When the Bluetooth module enters the data transmission working mode, its corresponding four pins are voltage pin VCC, data output pin TX, data input pin RX, and module GND. When the hardware circuit is connected, the data input pin TX of the corresponding Bluetooth module shall be connected with the data output pin RX of the single chip microcomputer, and the corresponding Bluetooth data receiving pin RX shall be connected with the data output pin TX of the single-chip microcomputer.

In the corresponding software algorithm flow architecture part, the corresponding algorithm implementation flow is shown in Figure 7. The main software algorithm flow includes the MCU initialization process, physiological data acquisition and analysis process, algorithm calculation and evaluation process, data transmission process, and data display and interaction process.

At the PCB design level of the hardware part, it mainly reduces the loss caused by reducing the corresponding parasitic parameters by simulating the corresponding parasitic parameters. At the same time, in the aspect of device selection, this paper mainly selects the chip with lower power consumption and reduces the loss of the overall hardware as much as possible in the aspect of device selection.

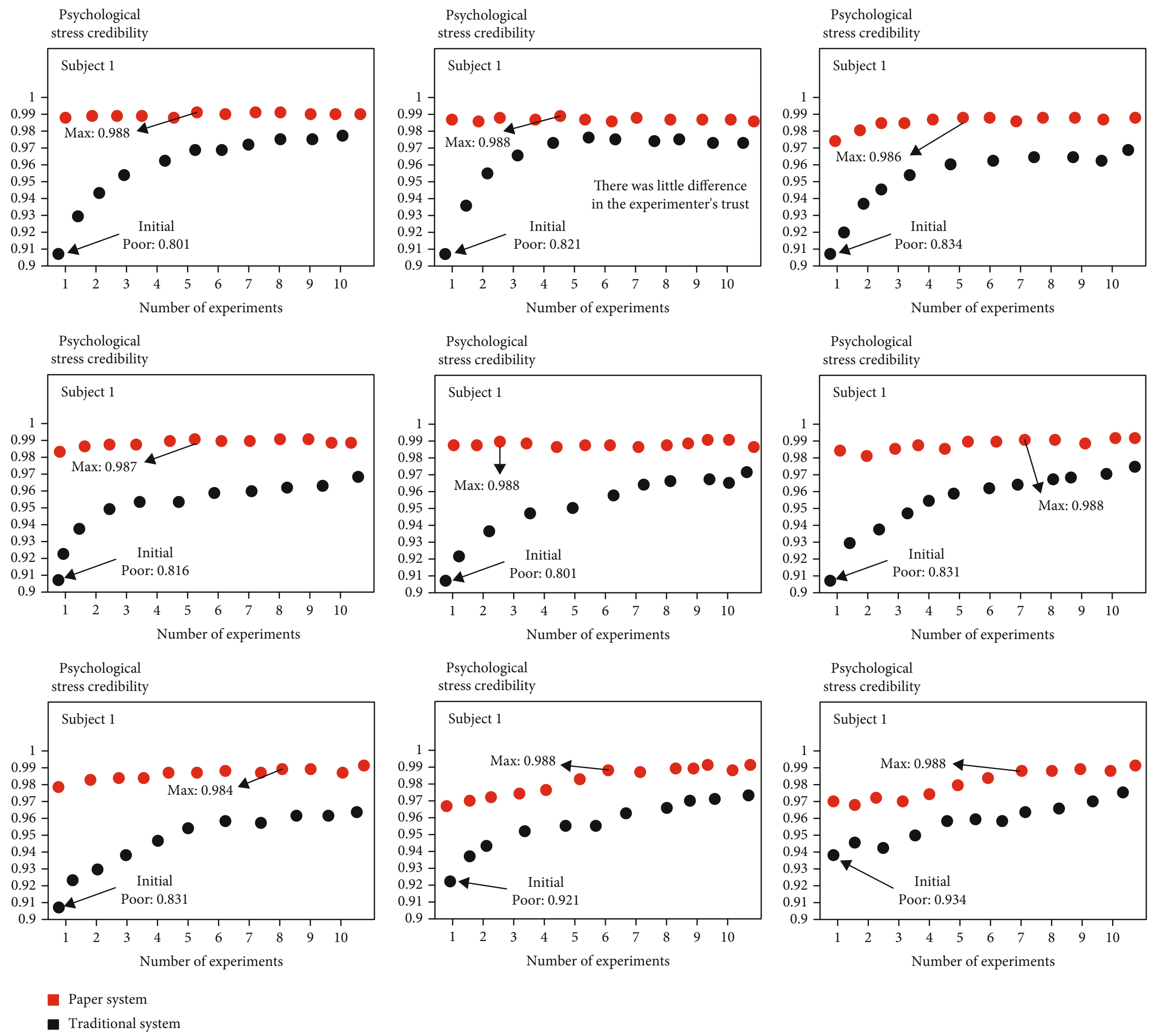

Figure 10: Psychological stress trust curve.

4. Experimental Verification and Data Analysis

The corresponding experimental environment and experimental conditions are as follows: the experimental subjects selected 9 students from related majors of a university as the experimental objects, mainly based on the system designed in this paper to collect their corresponding physiological parameters, such as ECG, EEG, and skin temperature, so as to ensure the normal mental health of the subjects before the corresponding experiment. There were no obvious emotional abnormalities. The corresponding experimental process is as follows: the wearable psychological stress monitoring system equipment based on a wireless sensor designed in this paper is worn to the participants, which calms the experimenters' mood for about 10 minutes before officially entering the experiment, records and stores the corresponding physiological parameter characteristics, and starts playing music from slow to fast after the calm transition period. The physiological parameters of the experimenters were recorded in real time, and their psychological stress level was evaluated.

The ECG, EEG, and skin temperature sampling values of the corresponding 10 college students in the quiet period are shown in Figure 8. It can be seen from the figure that the physiological parameters of the participants in the experiment are basically stable in the current state. At the same time, the psychological stress measurement under the psychological stress evaluation algorithm is a low value, which is more in line with the actual phenomenon.

After the calm period, the corresponding physiological parameters of the experimental participants in the corresponding psychological stress simulation period are shown in Figure 9. It can be seen from the figure that during this period, the corresponding physiological parameters of each participant generally accelerated, the corresponding ECG and EEG signal fluctuations increased significantly, and the skin temperature of the corresponding participants increased significantly.

Based on the above monitoring data and compared with the traditional psychological stress assessment algorithm, the corresponding psychological stress trust curve is shown in Figure 10. It can be seen from the figure that the corresponding psychological stress trust value of most experimental participants in the psychological stress simulation period is improved by 0.187 percentage points compared with the corresponding accuracy of the traditional algorithm, and part of the trust can reach 0.988. Therefore, the wearable psychological stress monitoring system based on a wireless sensor and its corresponding psychological stress evaluation algorithm proposed in this paper have obvious advantages.

Based on the experimental results and experimental data analysis, it can be concluded that the wearable psychological stress monitoring system based on a wireless sensor and the psychological stress identification algorithm based on multiphysiological parameter fusion decision-making based on evidence theory have obvious advantages over the traditional psychological stress estimation system, and its corresponding system reliability and analysis accuracy are significantly improved; therefore, the system has popularization value.

5. Conclusion

This paper mainly analyzes the current research status of individual psychological stress monitoring equipment and data analysis and expounds the problems existing in the traditional psychological stress monitoring technology. Based on the research status, based on the continuous development of microwireless sensor network technology, a wearable psychological stress monitoring device based on a wireless sensor is proposed, and an analysis algorithm is proposed based on the corresponding data analysis. At the hardware level of the system, this paper selects miniaturized and low-power microphysiological sensors to monitor the psychological pressure level discrimination indicators such as human heart rate, temperature, and heart rate waveform, fully optimize the layout of wireless sensors, realize the high efficiency, high transmission rate, and anti-interference performance of the system, and collect human pulse signals and heart rate signals through the sensor data acquisition module. The temperature signal is filtered and amplified, and analog-to-digital conversion is carried out at the same time, so as to realize the accurate measurement of key signals. At the system software level, this paper innovatively proposes a psychological stress identification algorithm based on multiphysiological parameter fusion decision-making based on evidence theory. By extracting the collected key signal features and identifying the primary stage of psychological stress, this paper finally realizes the evaluation and analysis of individual psychological stress through evidence theory. The experimental results show that the trust degree of an individual psychological stress test is improved by 0.187 compared with the traditional algorithm, and the corresponding psychological stress trust degree is up to 0.988, which has obvious advantages. In the follow-up, this paper will comprehensively analyze individual psychological stress based on more physiological data and further optimize the wearable psychological stress monitoring and data analysis system to realize the intellectualization and sustainable development of the system.

Data Availability

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

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

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