An internet of things-enabled wearable device for stress monitoring and control

Gulnur Tyulepberdinova[1], Ainur Abduvalova[2], Murat Kunelbayev[1], Gulshat Amirkhanova[1], Saltanat Adilzhanova[1]

[1]Department of Artificial Intelligence and Big Data, Faculty of Information Technology, Al-Farabi Kazakh National University, Almaty, Kazakhstan
[2]Department of Information Systems, Faculty of Information Technology, M.H.Dulaty Taraz University, Almaty, Kazakhstan

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ABSTRACT

The development of a wearable sensor device integrated into the internet of things (IoT) infrastructure is presented, with functionality aimed at continuous measurement of the user's physiological parameters and their intelligent processing for real-time stress level assessment. The system enables continuous monitoring of physiological parameters, allowing early detection of stress signals and supporting adaptive behavioral responses. The hardware platform is designed to consolidate various biomedical sensors, enabling continuous acquisition and intelligent processing of physiological data in real time. During testing, heart rate (HR) ranged from 68 to 89 beats per minute (bpm), respiratory rate varied from 11 to 15 breaths per minute, and skin conductivity ranged from 63 to 77 µS. Acquired physiological data were uploaded to a cloud-based infrastructure to enable advanced processing and analysis. The system achieved an overall stress detection accuracy of 87%, and signal stability remained high even under changing conditions. The proposed wearable solution demonstrates strong potential for use in healthcare, education, and occupational environments. It also offers scalability through the integration of intelligent algorithms and additional sensor modules.

Corresponding Author:

Gulnur Tyulepberdinova
Department of Artificial Intelligence and Big Data, Al-Farabi Kazakh National University
Almaty, Kazakhstan
Email: tyulepberdinova@gmail.com

1. INTRODUCTION

With the rapid advancement of digital technologies and the increasing demands of modern life, the issue of chronic stress is becoming ever more pressing. Prolonged exposure to stress has a detrimental impact on human health, increasing the risk of cardiovascular diseases, depressive disorders, anxiety, and cognitive decline. As a result, there is a growing need for modern solutions that enable continuous monitoring and effective management of stress levels in everyday life. Contemporary wearable devices and internet of things (IoT) technologies present vast opportunities for the development of intelligent systems that can track the physiological state of the human body in real-time. The integration of sensor components, physiological data processing algorithms, and wireless communication technologies enables the creation of personalized solutions for early stress detection and timely feedback to the user. According to Taskasaplidis *et al.* [1], it is noted that stress significantly affects human health and productivity. Modern wearable sensors enable non-invasive monitoring of stress in daily life. The article reviews detection methods and technologies and outlines prospects for further research. The article [2] discusses allostatic load, the long-term wear on the body caused by chronic stress responses. While allostasis helps maintain stability through change, prolonged activation of physiological systems such as the hypothalamic pituitary adrenal (HPA) axis and autonomic nervous system can harm overall health. In the study [3], it is shown that chronic exposure to stress hormones at different life stages affects brain structures related to cognition and mental health. The specific effects depend on the timing and duration of exposure, as well as genetic factors and environmental conditions. Stressors are recognized as key factors influencing human mood, behavior, and overall health [4]. Acute stress can be adaptive in healthy individuals, whereas prolonged or repeated exposure contributes to adverse health outcomes, with the effects shaped by genetic predisposition, coping mechanisms, and psychosocial resources. The article examines theoretical and empirical approaches to studying chronic stress through the allostatic load model [5]. In addition, it analyzes risk and protective factors and proposes strategies that contribute to successful aging. In article [6], the trier social stress test (TSST) is presented as an effective method for modeling psychological stress, inducing pronounced hormonal and physiological changes, including elevated cortisol levels and increased heart rate (HR). The findings demonstrate the influence of sex, genetics, and nicotine consumption on stress resilience, making this test a valuable tool for psychobiological research.

In study [7], the TSST is presented as a validated tool for modeling acute stress under experimental conditions. It has revealed biological, genetic, and age-related differences in stress responses and remains the gold standard for investigating acute stress in humans. In article [8], an overview of the effects of various methods on stress responses (cortisol levels) is presented, along with a step-by-step guide for conducting the TSST. This format can serve as a useful resource to enhance the scientific validity of future psychobiological stress research. In review [9], conducted using the preferred reporting items for systematic reviews and meta-analysis (PRISMA) methodology, the application of the TSST protocol was examined and variations across studies were identified. Standardization of procedures and reporting is recommended to enhance reproducibility and comparability of results. The article [10] summarizes current approaches to assessing heart rate variability (HRV) across different time scales and its importance for health and performance. It reviews time-domain, frequency-domain, and nonlinear measures, along with published normative values. The authors emphasize that HRV indicators depend on measurement context and are not directly interchangeable. In study [11], the foundations for standardizing the measurement and interpretation of HRV were established. This work, the result of collaboration among leading scientific societies, played a key role in advancing its application in both research and clinical practice.

In article [12], a new wrist-worn sensor was developed for long-term assessment of electrodermal activity (EDA) outside the laboratory, demonstrating high correlation with an FDA-approved system under various stressors. Electrode material testing confirmed that the distal forearm is a viable alternative to palmar sites for EDA measurement. The device enables comfortable long-term monitoring and offers promising opportunities for the diagnosis and investigation of psychoneurological conditions. In article [13], an approach to developing a personal healthcare system for stress detection using EDA is presented. In a study with 33 participants in an office environment, a wearable device was used to differentiate between cognitive load and stress induced by time-pressured arithmetic tasks and social-evaluative threat. Data analysis showed that EDA peak characteristics reflect stress levels, and classifiers achieved an accuracy of up to 82.8%, confirming the feasibility of monitoring stress phases throughout the working day.

This volume [14] presents updated data on brain imaging methods such as positron emission tomography (PET) and functional magnetic resonance imaging (fMRI), offering deeper insights into the neural mechanisms of EDA. It also summarizes hypotheses that have since been reliably tested. In article [15], a high-precision device for measuring EDA with 4 channels and a sampling rate of up to 100,000 samples per second was developed. It is operated through the AcqKnowledge software, supports data export and video synchronization. The device is widely used in clinical practice, neuropsychology, and can also function as a 4-channel electroencephalography (EEG) sensor. In study [16], the accuracy of seven commercial wrist-worn devices for measuring HR and energy expenditure (EE) was evaluated, and a system for their assessment was proposed. Sixty volunteers participated, using the Apple Watch, Basis Peak, Fitbit Surge, Microsoft Band, Mio Alpha 2, PulseOn, and Samsung Gear S2 under various activities. The devices measured HR more accurately than EE: the mean HR error during cycling was <5% for six models, while EE errors did not exceed 20%. The Apple Watch showed the highest overall accuracy, whereas the Samsung Gear S2 was the least accurate. The authors conclude that wearable devices are reliable for HR measurement but limited in EE estimation, and they propose reference standards for validating such technologies.

In article [17], stress-related devices were developed. A total of 1,773 HR measurements (49–200 beats per minute (bpm)) were recorded, with 27 data points missing due to technical limitations. Compared with ECG, accuracy varied: basis peak tended to overestimate HR during moderate exercise, whereas Fitbit Charge underestimated HR at higher intensities. Bland–Altman analysis revealed considerable variability during exercise; for the Apple Watch and MioFuse, 95% of differences with ECG were within –27 to +29 bpm, for the Fitbit Charge HR within –34 to +39 bpm, and for the basis peak within

–39 to +33 bpm. Body mass index, age, and sex did not affect measurement accuracy. In study [18], a 24-hour evaluation of the accuracy of the Apple Watch 3 and Fitbit Charge 2 was conducted under real-world conditions. Both devices demonstrated acceptable HR accuracy but tended to underestimate values and showed reduced precision at higher HRs and with unstable wrist movements. While they cannot replace ECG as the gold standard, they can serve as a supplement in clinical practice and research, particularly for large-scale data analysis. In study [19], the accuracy of the Polar OH1 was evaluated against ECG during moderate- and high-intensity exercise, and the feasibility of wearing it on the temple as an alternative to the forearm and upper body was examined. Twenty-four participants performed treadmill and cycling exercises while HR was recorded simultaneously by ECG and Polar OH1 at three body sites. Data were compared using Bland–Altman analysis and intraclass correlation.

In study [20], the accuracy of the Polar OH1 and Fitbit Charge 3 in measuring HR at rest and during different levels of physical activity was evaluated. Twenty adults participated in two trials: the first included a sedentary period, cycling on an ergometer, and a treadmill graded exercise test; the second involved short sprints on both a cycle ergometer and a non-motorized treadmill. Device data were compared with the criterion Polar H10 using Bland–Altman analysis, Pearson's correlation, and mean absolute percentage error. In study [21], a cloud-based vision of global IoT deployment is presented, discussing key technologies and application areas, as well as an implementation using Aneka based on the interaction of private and public clouds. The importance of converging WSN, the Internet, and distributed computing for future research is emphasized.

In document [22], advancements in IoT-based healthcare are reviewed, covering architectures, applications, and industry trends. Security and privacy issues are analyzed, including requirements, threat models, and attack taxonomies, with a collaborative security model proposed. The paper discusses the role of big data, smart environments, and wearable devices, as well as global eHealth policies. It highlights IoT's contribution to sustainable development and outlines future research directions. In article [23], a wearable healthcare system 2.0 is proposed for next-generation medical services. The core component is washable smart clothing with embedded sensors and electrodes that collect users' physiological data, while cloud-based machine intelligence analyzes their health and emotional status. The article [24] discusses wireless sensor network (WSN) technologies as the foundation of ubiquitous healthcare, providing continuous monitoring, contextual awareness, and alerts on abnormal conditions. These systems reduce the need for caregivers, support chronically ill and elderly individuals, and ensure quality care for children. Several modern examples are presented, along with an analysis of key requirements—such as unobtrusiveness, scalability, energy efficiency, and security/privacy—highlighting both the benefits and the remaining challenges. In article [25], key technologies—sensing, communication, and data analysis—are examined for their roles in healthcare, safety, home rehabilitation, treatment evaluation, and early diagnosis. The integration of wearable and environmental sensors is also discussed, along with future steps toward clinical implementation. In article [26], several low-cost and non-invasive systems for health and physical activity monitoring reported in recent years are presented and compared. The paper also reviews textile-based sensors with potential applications in wearable systems, the compatibility of different communication technologies, and future prospects and research challenges in remote monitoring systems. In article [27], a review of recent methods and algorithms for analyzing data from wearable sensors used in physiological monitoring within healthcare is presented. The paper discusses key data mining tasks such as anomaly detection, prediction, and decision support, with a focus on continuous time-series analysis. It also examines the suitability of specific machine learning (ML) techniques, reviews properties of datasets used for experimental validation, and identifies major challenges in applying these methods to health monitoring systems. In article [28], recent big data applications using physiological signals to support medical decision-making in both clinical and home settings are reviewed. The focus is on systems designed for continuous monitoring of patients in intensive care units, with a discussion of the challenges that must be addressed for clinical implementation. Once resolved, these systems have the potential to transform healthcare management in future hospitals. In article [29], a review of data fusion methods and algorithms for interpreting wearable sensor data in health monitoring applications is presented. The paper discusses applications in healthcare, including physical activity monitoring, ambulatory monitoring, gait analysis, fall detection, and biometric monitoring. It also provides an overview of commercially available sensors with a focus on their capabilities and highlights gaps that must be addressed to bring research to market. In article [30], portable biosensors were evaluated for monitoring physiological changes and health status. The findings show their potential for detecting early disease markers, circadian variations, and insulin sensitivity differences, highlighting their role in improving health monitoring and accessibility of medical care. In study [31], wearable and stress affect detection (WESAD) is introduced as a multimodal dataset for stress and emotion recognition using wearable devices. It includes data from 15 participants and achieves up to 93% accuracy in stress classification. In article [32], the cStress model is presented, developed through all stages of computational modeling, from data collection and preprocessing to training. The model was trained on laboratory data from 21 participants and validated on two independent datasets with 26 and 20 participants. It achieved 89% recall with 5% false positives in the lab and up to 72% accuracy in field studies. In study [33], recent works on stress detection in daily life using smartphones and wearable devices are reviewed. Unlike the numerous laboratory studies, such research is limited, and the studies are categorized by physiological methods and target environments such as office, campus, vehicle, and everyday settings. The paper also discusses promising approaches, mitigation strategies, and research challenges. In study [34], a context-based stress detection method was developed to enable continuous and unobtrusive monitoring in real life. The approach combines a laboratory-trained stress detector, an activity recognizer, and context-dependent analysis to make final decisions every 20 minutes. Experiments on 55 days of real-life data showed 70% recall of stress events with 95% precision.

The objective of this research is to develop a wearable device integrated with IoT technology for measuring stress levels.

2. METHOD

Real-time monitoring and management systems (RPMS) play a vital role in medical monitoring and patient health management. Obtaining accurate and reliable patient data requires the use of sensors that meet medical standards and provide both precision and stability. Such sensors must be capable of detecting subtle physiological changes while reducing the likelihood of false readings. Common examples in medical practice include HR monitors, blood pressure sensors, glucose meters, and accelerometers for tracking physical activity [35].

2.1. Research methodology

An IoT-based stress monitoring system was developed in this study using a wearable device equipped with nine embedded sensors, including photoplethysmogram (PPG), galvanic skin response (GSR), EEG, electrocardiogram (ECG), electromyogram (EMG), temperature, pressure, HR, and glucose sensors. The core control unit of the device is a microcontroller based on an field-programmable gate array (FPGA) platform.

In this approach, physiological signals such as HRV, skin conductance, and respiration rate are not only processed and transmitted to the cloud for advanced analysis but also enhanced through integrated noise suppression and ambient light compensation mechanisms of the MAX30102 sensor, which significantly improves the reliability of stress detection in real-world conditions.

We employ a wrist-worn multimodal setup (PPG MAX30102, ECG, GSR, skin temperature, and 3-axis IMU). Signals undergo band-pass filtering and detrending, motion-artifact reduction using IMU references, and per-subject z-score normalization. Features include HR/PR, HRV/PRV (RMSSD, SDNN, and pNN50), LF/HF, dPPG, GSR tonic/phasic indices (SCR count/amplitude), short-term skin-temperature trend, and activity cues. Stress is predicted by a Random Forest with mRMR feature selection and class-balance handling (logistic/SVM as baselines; LOSO cross-validation). Full step-by-step settings and ablations are provided in results and discussion to avoid redundancy.

The system utilized multiple ML algorithms to classify physiological data. Among them, the random forest method demonstrated the highest classification accuracy, outperforming other models in both precision and consistency. To improve hyperparameters CCC and γ\gammaγ were optimized using a grid search approach. The evaluation of each model included two key performance metrics: overall classification accuracy and resistance to signal noise. Final results were visualized through a custom-developed web application built on the Firebase platform, which enabled real-time data acquisition, monitoring, and interactive graphical representation of stress-related parameters.

The innovative aspect of this research lies in creating and deploying a wearable biomedical system architecture based on FPGA technology, enabling real-time parallel processing of data from a multi-sensor module. In contrast to conventional systems that predominantly depend on microcontroller-based data acquisition with limited computational resources, the proposed wearable solution is built on a programmable logic platform, offering significant architectural and functional advantages. This platform enables high-speed, hardware-level preprocessing of physiological signals, ensuring real-time performance with minimal latency. It supports energy-efficient operation by optimizing data flow and reducing computational overhead. Furthermore, the system integrates data from multiple biosensors—such as PPG, EMG, GSR, temperature, and acoustic sensors—to facilitate comprehensive, multifactor analysis of physiological states. A hybrid data management framework has been implemented, allowing simultaneous on-device signal visualization and storage while also providing remote access through a cloud-based web server and database interface. This architecture ensures scalability and enables seamless integration into existing telemedicine ecosystems and broader infrastructures.

This work proposes a framework for intelligent wearable devices that integrates hardware-based processing, adaptive sensor fusion, and secure data communication to enable continuous monitoring and early detection of stress-related conditions

The proposed system provides a novel integration of parallel signal processing and hardware-level computation, enabling real-time physiological analysis even under restricted power and resource conditions. By aggregating and interpreting multiple biosignals— temperature, and electromyographic activity—it ensures a multifactor evaluation of psychophysiological states, thereby enhancing the reliability. This work contributes to the advancement of wearable biomedical electronics by shifting the paradigm from single-function devices to multifunctional, adaptive platforms capable of personalized health monitoring. Furthermore, the system lays the groundwork for future developments in intelligent healthcare technologies, including predictive diagnostics, cyber-physical healthcare systems, and artificial intelligence (AI)-driven personalized medicine.

Thus, the proposed solution focuses on energy-efficient and intelligent wearable technologies capable of autonomous operation and seamless integration into digital healthcare ecosystems.

The device is manually activated by the user. Biosignals from the photoplethysmographic (PPG) sensor are transmitted to a processing module in real time for feature extraction. The integration of sensors within a compact wearable platform allows for the simultaneous monitoring of cardiovascular activity and stress-related physiological changes. The PPG sensor illuminates the skin and measures variations in reflected light intensity, which correspond to fluctuations in blood volume and oxygen saturation—key indicators of circulatory function. In parallel, changes in skin conductance, driven by sympathetic nervous system activity and sweat gland response, are also recorded. Under stress conditions, elevated sympathetic arousal increases perspiration, resulting in measurable shifts in skin conductivity. By capturing both cardiovascular and electrodermal responses, the system provides a comprehensive view of the user's physiological and emotional state (see Figure 1 [36]).

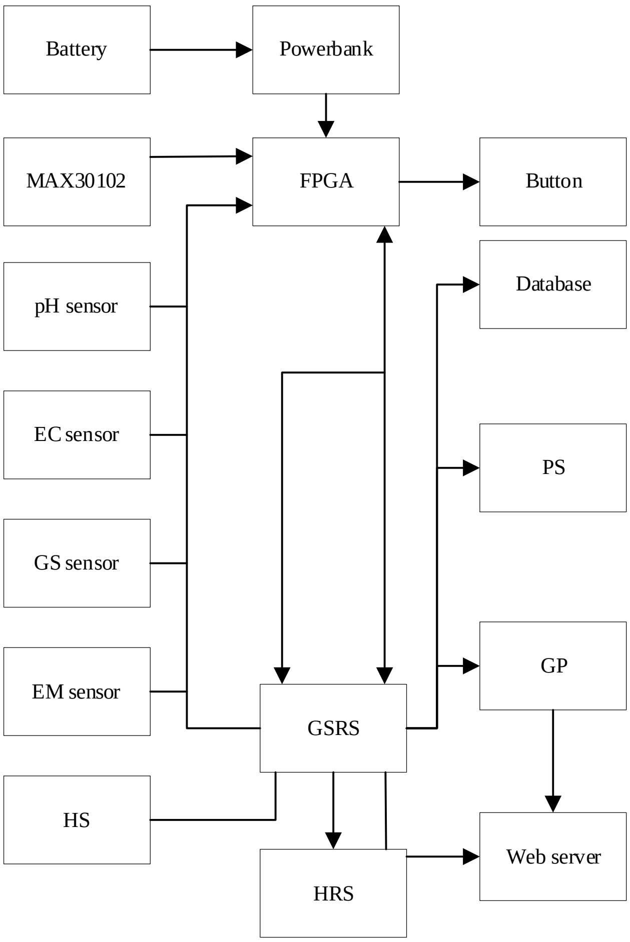


Figure 1. Block diagram of the wearable device with IoT integration for real-time stress monitoring

Figure 2 shows a wearable device designed for monitoring physiological parameters. It includes an ESP32 microcontroller, an OLED display for real-time data visualization, two Li-Po batteries, and a TP4056 charging module. The device features a GSR sensor (for measuring skin conductance), a PPG sensor (located underneath for detecting blood volume), and a DS18B20 temperature sensor. All components are housed in a compact enclosure with Velcro straps for easy attachment to the body, and the system is controlled via a side-mounted switch.

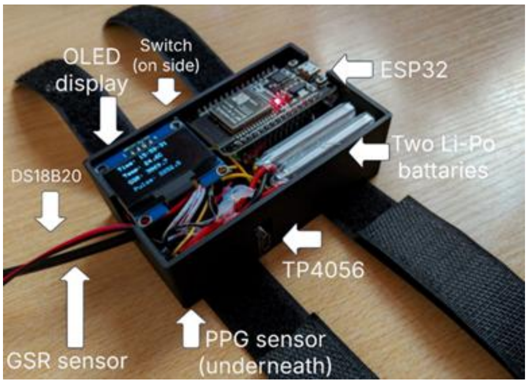


Figure 2. Design of the wearable device

In contemporary wearable technologies, including smartwatches, fitness trackers, and medical bands, the MAX30102 and GSR sensors are frequently employed [36]. These sensors make it possible to continuously monitor critical physiological parameters such as HR, oxygen saturation, and stress indicators. A notable advantage of the MAX30102 is the integration of noise reduction and ambient light compensation, which ensures reliable signal acquisition even in dynamic environments, for instance, during physical activity or under fluctuating illumination. This characteristic underlines its relevance for both consumer and medical-grade devices [37]. Additionally, the sensor can be adapted to different skin tones and environmental settings, thereby improving measurement precision across diverse user groups. When combined with GSR technology, its incorporation into IoT-based platforms offers the potential for real-time physiological monitoring and cloud-supported data analytics [31].

Stress and respiration are closely related, as breathing typically accelerates during stressful situations to support circulation. This effect can worsen respiratory conditions such as asthma or emphysema. Increased sympathetic nervous system activity also enhances sweat gland function, leading to higher skin conductance. Figure 3 illustrates the relationship between respiration and conductance.

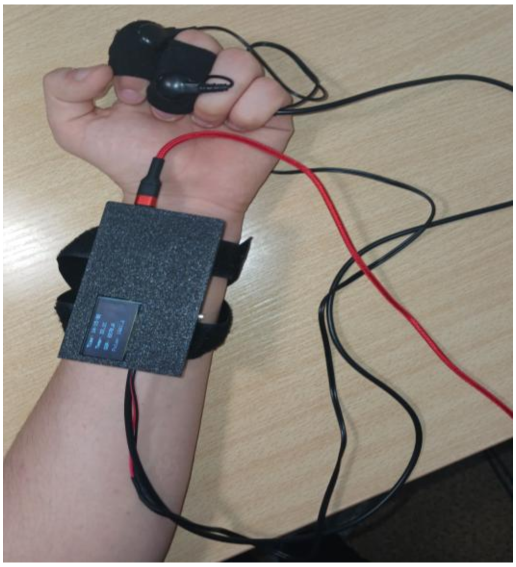


Figure 3. A wearable device attached to the subject's forearm with a strap

Figure 3 illustrates a wearable device fastened to the subject's forearm with a strap. The device is connected to sensors attached to the fingers, such as PPG or GSR sensors. The connecting cables link the sensors to the main unit, which, equipped with a display, supports the collection, visualization, and potentially the transmission of physiological data. This type of device is employed to monitor stress-related parameters and cardiovascular activity. Stress can temporarily increase both HR and blood pressure, and sustained hypertension elevates the risk of heart attacks by damaging arteries and promoting blood clot formation.

To accurately interpret HR data obtained from wearable sensors, it is essential to consider age-based physiological norms. The average resting HRs for different age groups are presented in Table 1.

Table 1 provides brief physiological explanations. Newborns and infants exhibit the highest HRs (90–180 bpm and 100–160 bpm, respectively) due to rapid growth and developing systems. As children age, their HRs gradually decrease, reflecting the maturation of the cardiovascular system and greater efficiency. By adolescence and adulthood, the normal range typically stabilizes between 60 and 95 bpm. Well-trained athletes usually have even lower resting HRs (40–55 bpm), indicating enhanced cardiac efficiency and conditioning.

Table 1. HR levels

Age group	Resting HR range (bpm)	Typical condition/notes
Newborn (0–1 month)	90–180	Rapid growth and high metabolic rate
Infant (1–11 months)	100–160	Developing nervous system
Toddler (1–2 years)	90–140	Active and mobile phase
Preschool (3–4 years)	85–125	Increased physical activity
Early school age (5–6 years)	80–115	More stable rhythms
Middle childhood (7–9 years)	75–105	HR slows with age
Adolescents and adults (10+ yrs)	60–95	Typical adult resting rate
Well-trained athletes	40–55	An efficient cardiovascular system

3. RESULTS AND DISCUSSION

To develop application the FPGA, Firebase can be utilized as the backend for data storage and synchronization, as well as for data visualization.

Figure 4 shows the architecture of a Firebase-based web application for displaying sensor data from an FPGA device. The FPGA uploads sensor data (such as HR or respiratory signals) via REST/HTTPS protocols. Firebase handles authentication (e.g., email and Google login), stores data in Firestore or Realtime Database, and optionally processes it using cloud functions. The web application retrieves this data in real-time via the Firebase SDK, manages user settings, and sends push notifications using Firebase cloud messaging (FCM). Additional services, such as storage and analytics, support media handling and user behavior monitoring.

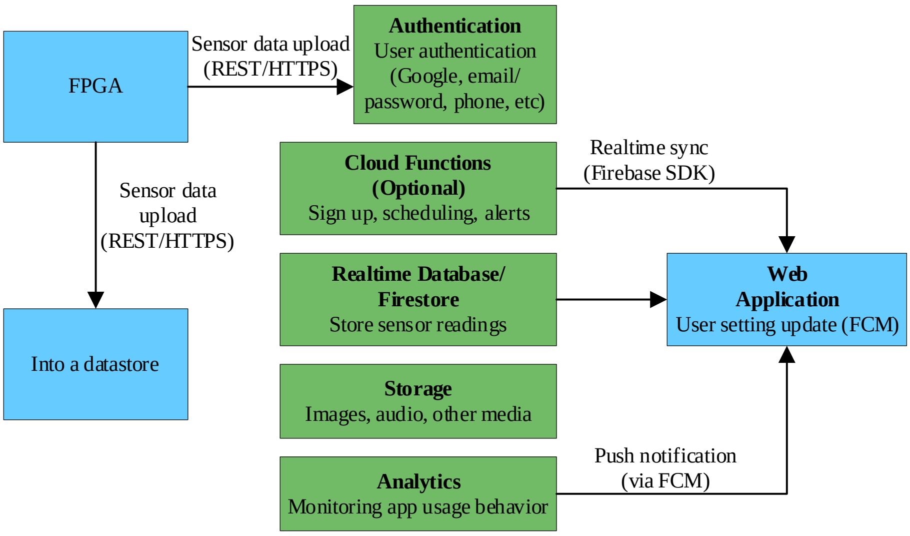


Figure 4. Cloud-driven web dashboard for displaying physiological sensor outputs

Figure 5 visually outlines the design of an experiment aimed at measuring physiological parameters under stress and rest conditions. It begins with the objective, followed by participant demographics, highlighting 30 healthy volunteers aged 20–45. The testing setup consists of three stages: rest, stress induction, and recovery, all conducted in a controlled laboratory environment using a wearable device. Data is collected at a rate of 1 Hz and stored in a real-time database. The final step involves control and validation using the perceived stress scale, as well as calibration with a reference HR monitor to ensure accuracy.

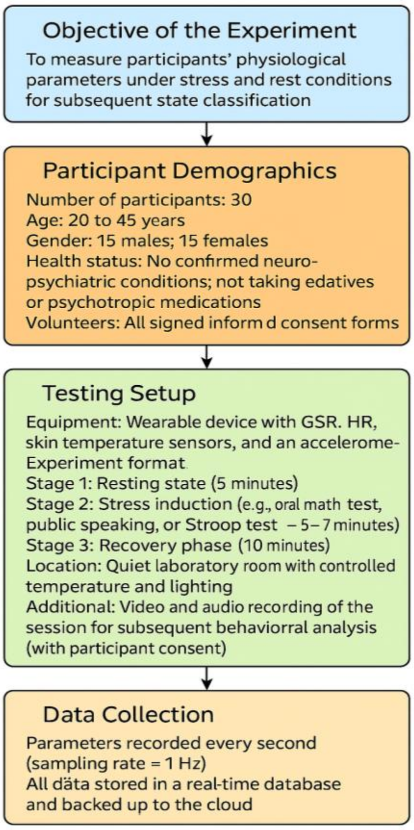
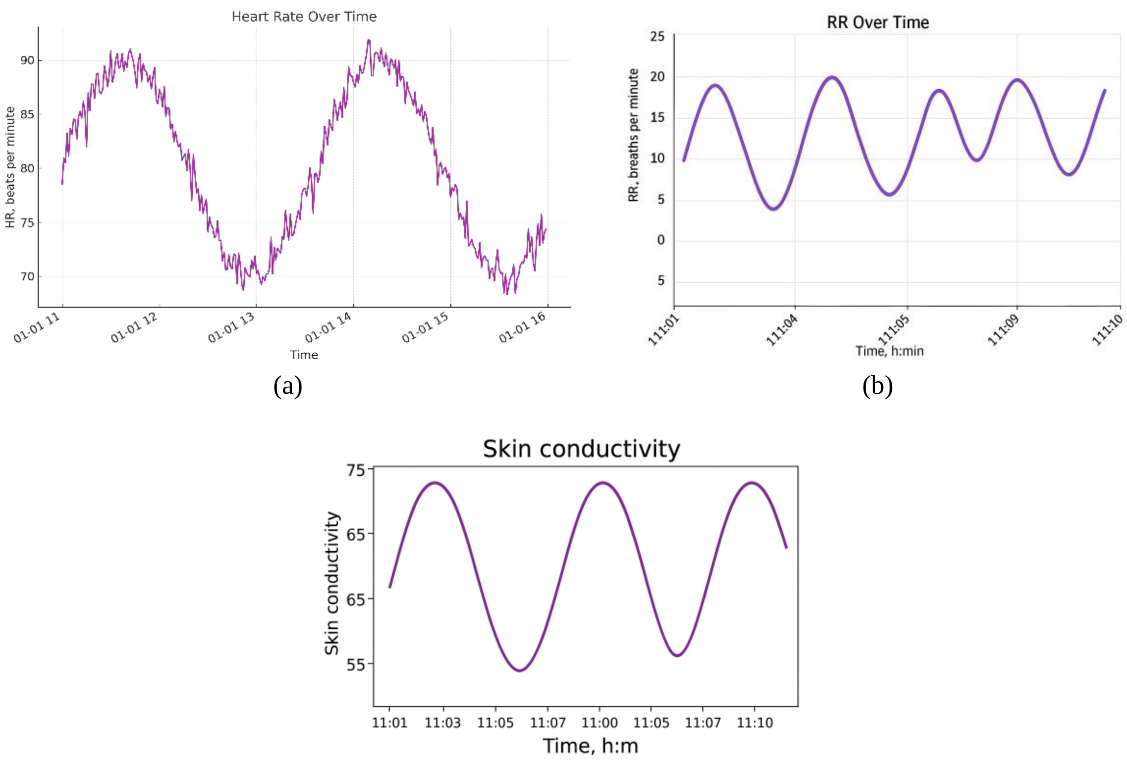


Figure 5. The design of an experiment aimed at measuring physiological parameters under stress and rest conditions

Figures 6(a) to (c) present the parameter values recorded over a 15-minute period. These results allow for the assessment and identification of potential fluctuations in physiological indicators influenced by various factors.

Figure 6(a) shows the dynamics of HR over 10 minutes — from 11:00 to 11:10. Initially, the HR is approximately 80 bpm, peaking at around 97 bpm at 11:02. After a slight decline, it stabilizes in the range of 82–88 bpm until 11:06, followed by another short rise. By the end of the observation period (1approximately 11:10), the HR returns to approximately 80 bpm. This curve may indicate a physiological response to moderate stress or physical activity. Figure 6(b) presents the respiration rate (RR) over the same 10-minute period — from 11:01 to 11:10. At the beginning, the breathing rate remains at 17–18 breaths per minute, then increases to a maximum of around 24 breaths/min near 11:04. It then decreases to approximately 16 breaths/min. It continues to fluctuate between 18 and 22 breaths per minute. By the end of the observation period (approximately 11:10), the value stabilizes at around 20 breaths per minute. This pattern may reflect a brief physical load or stress-related physiological response. Figure 6(c) shows the dynamics of skin conductance during the 10-minute period — from 11:01 to 11:10. At the start of the measurement, skin conductance is about 62 µS, rising to a maximum of approximately 74 µS around 11:02. After a short drop to 60 µS at 11:03, periodic fluctuations occur between 61 and 73 µS. Toward the end of the observation, values stabilize in the range of 62–64 µS. Such fluctuations in skin conductance may indicate a transient stress response or changes in arousal level.



(a) (b)

(c)

Figure 6. Measured physiological parameters displayed over 15 minutes; (a) dynamics of HR over 10 minutes; (b) respiration rate (RR) over 10 minutes; and (c) dynamics of skin conductance over 10 minutes

Figure 7 displays glucose levels predicted using the double moving average method under normal conditions. Monitoring plasma glucose levels in older adults shows that pre-meal glucose levels typically fall within the range of 90 to 130 mg/dL, while post-meal levels can rise to as much as 180 mg/dL. According to the International Diabetes Federation, two groups are analyzed: independent patients and those who are functionally dependent.

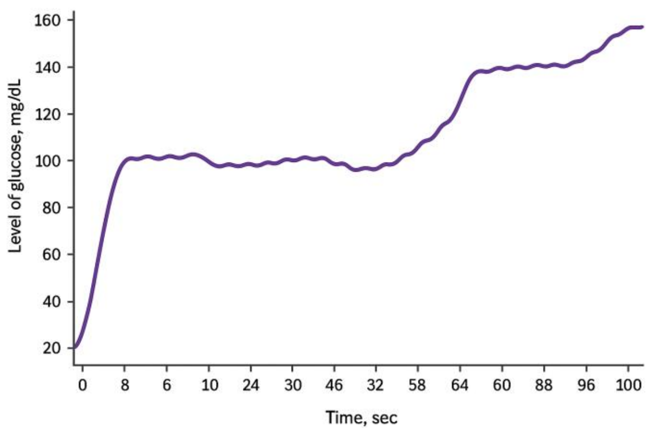


Figure 7. Glucose concentrations represented as averages in normal state

Figure 8 shows an ECG signal recorded over 100 seconds, with an amplitude ranging from 55 to 130 μV. Six distinct QRS peaks are visible, representing heart contractions occurring approximately at the 9th, 38th, 46th, 56th, 66th, and 74th seconds. The average signal amplitude fluctuates within the range of

70–80 µV, which corresponds to the baseline level between the peaks. Analysis of such a signal can be used to assess heart rhythm and stress levels in health monitoring systems.

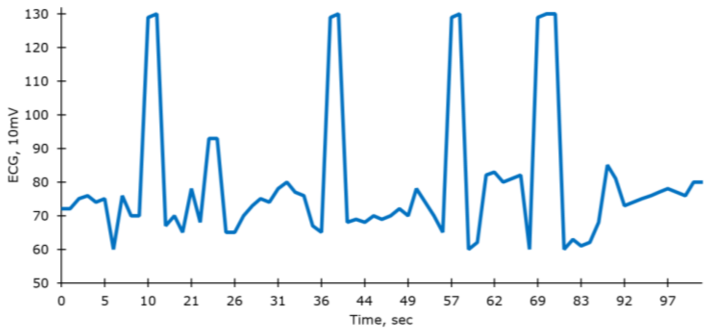


Figure 8. Normal electrocardiographic readings

It includes hardware integration of multiple biosensors, signal acquisition and processing, implementation of a custom stress monitoring algorithm (SMA), and ML-based classification. A detailed comparative analysis demonstrates the classification accuracy of the system's technologies, indicating its potential as a promising tool for continuous stress assessment in daily life.

Table 2 presents a performance comparison of the key characteristics of four different physiological monitoring systems. The proposed IoT-based wearable device demonstrates an accuracy of 87%, which is higher than that of commercial fitness bands (78%) and smartwatches with HR and GSR sensors (82%), but slightly lower than that of a chest strap heart monitor (90%). The device's response time is 250 ms, significantly faster than most competitors, including fitness bands (500 ms). Its power consumption is 120 mW, placing it in a moderate range between more energy-efficient solutions and high-performance but power-intensive chest monitors (150 mW). Thus, the proposed system offers a well-balanced trade-off between accuracy, response time, and power efficiency.

Table 2. Performance comparison (accuracy, response time, and power consumption)

Device/system	Accuracy	Response times, ms	Power consumption
Proposed wearable (IoT-based)	87	250	120
Commercial fitness bend	78	500	95
Smartwatch with HR&GSR	82	400	110
Chest starp HR monitor	90	300	150

For the proposed IoT-enabled wearable device, a statistical evaluation of accuracy was conducted based on 10 measurements. The average accuracy was 87.05%, with a standard deviation of ±0.52%. According to the calculations, the 95% confidence interval ranges from 86.68% to 87.42%. This confirms the stability and reliability of the system's accuracy under repeated measurement conditions.

In real-world applications of wearable stress monitoring devices, two significant challenges often arise: motion artifacts and latency. Motion artifacts are distortions in biosignals caused by the user's physical activity, such as walking, bending, or arm movements. These artifacts can significantly affect the accuracy of HR, pulse variability, or skin conductance measurements. To reduce the impact of such distortions, accelerometers and signal filtering algorithms are used. Latency occurs during the stages of data acquisition, processing, and transmission, and is particularly critical for systems operating in real-time. It can result from buffering, microcontroller computation time, or delays in wireless communication. To minimize latency, local data processing, algorithm optimization, and modern communication protocols (such as BLE 5.0) are applied.

Hardware and network limitations for real-world deployment of wearable stress monitoring devices:

a. Hardware limitations:
- Limited computational resources: microcontrollers (e.g., ESP32) have limited performance, which makes it challenging to run complex ML models in real-time.
- Limited memory capacity: restrictions on RAM and non-volatile memory hinder the storage of large datasets or long-term logging without data offloading.

- Power supply and autonomy: battery-powered operation requires energy optimization, limiting data acquisition frequency and the use of power-intensive sensors (e.g., infrared cameras).
- Sensor quality: low-quality sensors can produce noisy data, particularly during movement, which reduces the accuracy of stress detection.

b. Network limitations:

- Low bandwidth: Bluetooth low energy (BLE) or other protocols may be insufficient for streaming high-resolution data.
- Transmission latency: data transfer to the cloud may be delayed due to unstable Wi-Fi or mobile networks.
- Security concerns: transmitting sensitive biometric data requires encryption, which adds extra processing load on the device.
- Lack of continuous connectivity: in real-world conditions, Wi-Fi or mobile network access may not always be available, especially in remote areas.

Future improvements in stress monitoring systems involve the use of advanced networks to enable more accurate and automated stress detection. A promising direction is the analysis of multimodal biosignals (e.g., HR, skin temperature, and physical activity), which can increase the reliability of diagnostics. Additionally, the development of personalized models tailored to individual users, as well as the implementation of energy-efficient communication protocols and edge computing, is expected. Integration with cloud platforms and mobile applications will enable real-time data visualization, stress reduction recommendations, and remote support from healthcare professionals.

Wearable devices developed for stress monitoring have the potential to be applied in a broader context of mental health care. For instance, they can be used for the early detection of anxiety disorders, depression, and burnout syndrome through long-term observation of physiological and behavioral parameters. hese devices can be integrated with telemedicine platforms, enabling physicians to monitor patient conditions and make informed adjustments. Additional applications include cognitive therapy**,** behavioral coaching**,** emotional state monitoring for children with ADHD or individuals with autism, as well as employee wellness and productivity systems in corporate environments.

The real-world deployment of AI-powered wearable devices for stress monitoring faces several limitations. First, the limited computational resources on such devices make it difficult to implement complex AI models, such as neural networks. Second, the high energy consumption of AI algorithms reduces the battery life of these devices. Additionally, issues related to privacy and security arise when transmitting and storing sensitive biomedical data. Future improvements may involve the use of lightweight models (such as MobileNet and TinyML) and edge AI adaptation to support profile-based personalized development. Moreover, advancements in energy-efficient neuromorphic chips will enable more accurate analysis without increasing power consumption. Integrating AI with cloud and hybrid architectures will further enhance real-time data analysis and interpretation capabilities.

Table 3 presents a comparative analysis of existing wearable devices, showing that the Apple Watch and Samsung Galaxy Watch incorporate built-in AI algorithms for personalized recommendations. The Fitbit Sense also tracks stress and ECG, providing a basic level of analysis. Garmin Vivosmart 4 and Xiaomi Mi Band offer basic physical activity and sleep tracking, but have limited intelligent capabilities. Thus, premium-class devices provide more accurate and adaptive data analysis through the use of AI.

Table 3. Comparative analysis of existing wearable devices

Device	Stress detection	HR monitoring	Sleep tracking	AI/smart analysis
Apple Watch Series	Yes	Yes	Yes	Advanced AI insights
Samsung Galaxy Watch	Yes	Yes	Yes	Personalized health insights
Fitbit Sense	Yes	Yes	Yes	Basic AI interpretation
Garmin Vivosmart 4	Limited	Yes	Yes	No smart interpretation
Xiaomi Mi Band	Limited	Yes	Yes	Minimal/no AI integration

In previous studies, various ML and AI methods have been widely applied to classify stress levels. Algorithms such as support vector machine (SVM), random forest, decision trees, CNN, and long short-term memory (LSTM) are widely adopted in stress detection research, demonstrating effectiveness in classification and prediction of physiological patterns.

a. SVM: used for binary and multiclass classification; it provides high accuracy when well-selected features are used.

b. Random forest: offers robust classification through an ensemble of decision trees and handles noisy data effectively.
c. Decision trees: interpretable rule sets, fast and lightweight, but prone to overfitting without regularization
d. CNN: extract spatiotemporal patterns from physio-signals/images; require sufficient training data.
e. LSTM: effectively model temporal dependencies and variability in physiological signals.

This study's approach differs from previous works in several key aspects:

a. Accuracy: the ML and/or neural network models were trained on an extended dataset that includes multichannel physiological signals (e.g., HR, GSR, and temperature), which significantly improves the classification accuracy of stress states compared to traditional single-sensor methods.
b. Efficiency: the system is implemented on an energy-efficient wearable device capable of real-time data processing, reducing latency and eliminating the need for constant connection to external servers, as seen in cloud-based solutions.
c. Usability: unlike bulky lab systems, the proposed solution features a compact form factor (e.g., wristband), a simple mobile application for users, and requires no special skills — it automatically collects, analyzes, and visualizes the data.

Thus, the proposed system offers an improved balance between technical accuracy, response speed, and everyday usability for end users.

The signal processing sequence in stress monitoring systems typically includes the following stages:

a. Acquisition and synchronization: stable sampling and artifact markers reduce the proportion of “bad” windows → HRV dispersion shrinks at the raw-data level and inter-session reproducibility improves.
b. Filtering and motion suppression: notch/band-pass filters plus IMU referencing increase PPG/ECG SNR → MAE(HR) decreases and the share of correctly detected peaks rises; models receive cleaner features, yielding gains in F1/AUROC.
c. Windowed segmentation: switching to short, overlapping windows stabilizes statistics (RMSSD, pNN50) and lowers system latency → less class jitter at state boundaries.
d. Feature extraction: adding informative time–frequency descriptors (e.g., LF/HF, SCR dynamics, dPPG) improves class separability → AUROC/F1 increase without heavier inference.
e. Normalization (inter- and intra-subject): personalized scaling suppresses inter-individual amplitude differences → variance of metrics across participants decreases and LOSO robustness improves.
f. Multisensor fusion: combining HRV + GSR + temperature/activity yields complementary cues → performance in ambulatory scenarios exceeds any single-sensor setup.
g. Classifier: after steps b–f, classical models (RF/SVM) provide a strong baseline, while neural models (CNN/LSTM) add further gains given sufficient data → better accuracy without brittleness to noise.
h. Post-processing/hysteresis: smoothing prediction probabilities and applying threshold logic reduce spurious state switches → the UI receives stable decisions near class boundaries.

This pipeline ensures accurate, robust, and interpretable real-time stress assessment.

In this work, we distinguish three main directions of classification: i) machine learning models, ii) threshold-based rules, and iii) a hybrid approach:

a. ML models: SVM: often used due to its robustness with small training datasets. Effective for binary classification: stress/no stress.
b. Random forest and decision trees: interpretable models that perform well with various types of features (e.g., GSR, HR, and ECG). KNN: a simple model applicable when sufficient training data is available. Logistic regression: used to estimate the probability of a person being in a stress state. Deep learning (LSTM and CNN): Applied to time series and ECG images, offers high accuracy but requires large datasets.
c. Threshold values: simple logic: for example, if GSR > 5 µS or HR > 90 bpm at rest, it is classified as stress. Can be set empirically or individually (based on calibration for a specific user).

In real-world systems, a hybrid approach is often used: initial filtering based on thresholds, followed by refinement using an ML model. This method improves accuracy and reduces false positives.

4. CONCLUSION

An intelligent wearable system for real-time stress monitoring and management is presented. The developed system demonstrates high accuracy in stress detection (87%), as validated by experimental results utilizing nine integrated biosensors and advanced ML algorithms. The use of an FPGA platform enables the parallel processing of multi-channel biosignals, improving the device’s energy efficiency. Integration with the Firebase cloud platform ensures convenient data access and facilitates further analytics. The practical significance of this research lies in creating a universal tool for personalized psychophysiological monitoring, which can be applied in healthcare, educational, and corporate environments. The system enables the early diagnosis of stress, the prevention of chronic diseases, and the development of personalized health management recommendations. Future research will focus on expanding the sensor module, implementing more advanced AI models, and integrating the system with mobile medical services. The method enhances adaptability and effectiveness in real-world scenarios, contributing to the advancement of digital healthcare and preventive medicine technologies.

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AUTHOR CONTRIBUTIONS STATEMENT

All authors contributed substantially to the development of this paper. Gulnur Tyuleperdinova and Ainur Abduvalova were responsible for conceptualization and supervision. Murat Kunelbayev and Saltanat Adilzhanova contributed to methodology and investigation. Gulshat Amirkhanova and Gulnur Tyuleperdinova performed the formal analysis. Murat Kunelbayev prepared the original draft, and all authors participated in reviewing and editing the manuscript. Gulnur Tyuleperdinova is the corresponding author and will handle all communication related to this work.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Gulnur Tyulepberdinova	✓			✓	✓		✓			✓		✓	✓	
Ainur Abduvalova			✓		✓		✓	✓		✓		✓		
Murat Kunelbayev		✓		✓		✓	✓		✓	✓				
Gulshat Amirkhanova			✓		✓		✓			✓	✓			
Saltanat Adilzhanova		✓				✓	✓			✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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BIOGRAPHIES OF AUTHORS

Gulnur Tyulepberdinova graduated from Al-Farabi Kazakh National University in 2002 with a Bachelor's degree in Applied Mathematics. In 2004, she graduated with a Master's degree from Al-Farabi Kazakh National University. Since June 30, 2011, the academic degree of Candidate of Physical and Mathematical Sciences has been awarded. She has more than 60 scientific papers, including publications with a non-zero impact factor, indexed in international information resources such as Scopus, as well as in publications recommended by the Ministry of Education and Science of the Republic of Kazakhstan. Main research areas: system analysis and mathematical programming problems, artificial intelligence, and big data. She can be contacted at email: tyulepberdinova@gmail.com.

Ainur Abduvalova graduated from M.H. Dulaty Taraz University with a Bachelor's degree in Information Systems. She later obtained her Master's degree from the same university, specializing in the field of digital technologies in education. She holds the academic degree of Candidate of Technical Sciences and currently serves as an associate professor in the Department of Information Systems. She has authored more than 50 scientific publications, including indexed articles in Scopus and journals recommended by the Ministry of Science and Higher Education of the Republic of Kazakhstan. Her research interests include internet of things (IoT), educational informatics, intelligent systems, and applied digital technologies in higher education. She can be contacted at email: azh.abduvalova@dulaty.kz.

Murat Kunelbayev received a Bachelor's degree in Radio Physics and Electronics from Al-Farabi Kazakh National University in Almaty, Kazakhstan, in 1997, and a Master's degree in Engineering from the same institution in 2003. He is currently a senior researcher at the Institute of Information and Computational Technologies, CS MES RK. He is also an editor and reviewer of many scientific journals. He has authored or co-authored more than 70 peer-reviewed journal and conference papers, 7 book chapters, and three co-edited books with Springer. His research interests include power system management, electronics, artificial intelligence, sensor technologies, and renewable energy sources. He can be contacted at email: murat7508@yandex.kz.

Gulshat Amirkhanova graduated from Al-Farabi Kazakh National University in 2001 with a Bachelor's degree in Applied Mathematics. In 2003, she graduated with a Master's degree from Al-Farabi Kazakh National University. She is a leading specialist in the fields of parallel computing and high-energy physics. Her scientific activity focuses on the development and implementation of advanced computational methods for solving problems related to data processing and analysis in high-energy physics experiments. She can be contacted at email: gulshat.aa@gmail.com.

Saltanat Adilzhanova graduated from Al-Farabi Kazakh National University in 2002 with a Bachelor of Science degree in Applied Mathematics. In 2004, she graduated with a Master's degree from Al-Farabi Kazakh National University. She is a recognized expert in the field of information technology and security, and has devoted her scientific activity to developing innovative approaches to resource management in the field of information security. She possesses a wealth of scientific and practical experience, making her research highly relevant to the modern digital society. She can be contacted at email: asaltanat81@gmail.com.