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Wearable Technology for Real-Time Monitoring of Stress and Behavior in Autistic Individuals in the USA

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Abstract. This research investigates the development and deployment of wearable technology to monitor stress and behavioral patterns in real time of patients with Autism Spectrum Disorder (ASD). Physiological and behavioral data are collected by wearable devices like smartwatches and biosensors and then analyzed with machine learning algorithms for improving personalized care and crisis management. These technologies address the needs of autistic individuals by facilitating autonomy, reducing caregiver burden, and improving health outcomes. In this mixed methods study, the effectiveness of these devices is evaluated based on quantitative metrics such as accuracy and usability and qualitative feedback from users and caregivers. The results suggest that stress detection and behavior tracking can be improved significantly and that scalable solutions in ASD care are possible.

Keywords: Autistic Individuals, Monitoring of Stress, Wearable Technology.

1. INTRODUCTION

1.1. Background

Autism Spectrum Disorder (ASD) is a developmental disability that involves impairments in social interaction, communication, and repetitive behaviors. Autism affects about 1 in every 36 children in the United States, a statistic that has been on the rise in the last few decades not only because of enhanced awareness but also because of improved diagnosis (Prevention, 2024). ASD is present in a spectrum, so it is vital to understand that people with this disorder experience a variety of symptoms, and the severities can vary greatly (Health, 2024). Some of the most critical issues that people with autism and their carers face are increased stress levels and an increased likelihood of experiencing unpredictable behaviors, which, if not addressed, may lead to crises(Khan et al., 2024).

The stress that is often observed in people with ASD is caused by sensitivity to certain stimuli, changes in the daily schedule, and problems with speaking (van der Linden et al., 2022). While patients and their families struggle to understand gestures, caregivers have a twofold task of recognizing the cues and knowing what leads to the episode(Mohammad, Khatoon, et al., 2024). Stress and behavior assessment have traditionally depended on self-reporting by caregivers or sporadic physician assessments, which, although important, could be highly subjective and lack timeliness (Kul & Kara, 2019). This gap has left a gap that requires new methods of ongoing, real-time stress and behavior tracking to facilitate early detection and thus enhance the quality of care(Gorgun, 2024a). Mobile or wearable technology has then been identified as a special approach to tracking the stress and behavior of patients with ASD. For example, smartwatches, biosensors, and other wearable devices can record physiological biomarkers, including HRV, SC, and physical activity (Hernández-Capistrán et al., 2024; Masoumian Hosseini et al., 2023; Vos et al., 2023). These physiological markers are aligned with stress and behaviors to help caregivers and clinicians understand the issues that ASD patients are experiencing. It also means that machine learning and wearable technology help recognize stress or any changes in behavior in real time and perform early actions (Koumpouros & Kafazis, 2019).

1.2. Challenges in Stress and Behavior Monitoring

Past research studies have shown that there are some difficulties in supervising stress and behavior in people with ASD. Due to its diverse presentation, symptoms, and stressors that define the condition also differ from one person to another (Muscatello et al., 2024). Some patients show stress in ways that are not immediately obvious, and in some cases, the caregivers may not even recognize these behaviors or mistake them for something else(Mohammad, Prabha, et al., 2024). Furthermore, conventional approaches to stress assessment are based on observations made by the caregiver and thus could be biased and inconsistent(Gorgun, 2024b).

Despite being more structured, clinical assessments at scheduled intervals can seldom provide the true picture of stress and behavior in natural contexts (Fuld, 2018). Stress and behavior changes may be observed several times a day due to environmental, sensory, or emotional stimuli(Nilima, Bhuyan, et al., 2024). Therefore, interventions that are dependent on retrospective outcomes may not catch important time points for action, making the approach more reactive than proactive. Furthermore, access to traditional monitoring is also a problem, including for families that live in rural areas or face difficulties reaching specialized autism care(Prova,

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2024b).

Wearable technology is a new approach to these challenges as it can provide constant objective measurement of physiological and behavioral data (Koumpouros & Kafazis, 2019). It can enable them to watch data in real-time and maintain a current record of stress and behaviors(Nilima, Hossain, et al., 2024). Compared to other practices, wearable devices are less invasive and are, therefore, suitable for ASD patients who cannot endure invasive monitoring practices. In addition, data collected by wearables can have patterns that the caregivers might not ascertain, making the. interventions more accurate(Prova, 2024a).

1.3. Advances in Wearable Technology

Smart clothing has been more developed in the last few years due to the improvements in sensor technology, data mining, and artificial intelligence. For instance, wearable technologies can help monitor some of the basic indices of persons with ASD, including HRV (Hernández-Capistrán et al., 2024; Li et al., 2023; Masoumian Hosseini et al., 2023), which is associated with ANS and the rate of stress(Görgün, 2024). SC also measures changes in skin conductance due to sweating to generate an index of emotional activity. Behaviors detected from movements captured by the wearables using accelerometers include pacing, fidgeting, or repetitive motions(Saha et al., 2024).

The linking of these data streams with machine learning is important as it enables one to discover patterns and correlations that may not be easily recognizable. For example, an increase in HRV coupled with repetitive movements may mean that stress is on the rise (Li et al., 2023). Therefore, caregivers should act before the stress level rises to another level(Shahana et al., 2024). Behavior trends can also be forecasted using machine learning models by applying data from previous behavior, and this will help caregivers and clinicians to have a way to intervene as per the model's suggestion. Devices with connectivity features, including Bluetooth or Wi-Fi, can easily sync data with Smartphones, clouds, or Healthcare providers. This connectivity enables monitoring from a distance so that parents and physicians can be notified concerning essential shifts in stress or behavior. In families and schools, especially where constant supervision of the children is not possible, such capabilities are very useful(Sharmin, Khatoon, et al., 2024).

1.4. Personalized Care and Crisis Management

Individualization remains a central approach to ASD treatment due to the variability of the symptoms and their requirements (Frye et al., 2022). Wearable technology could be described as having the capacity to transform individualized attention by offering third-party, real-time information that can be used in decision-making(Gorgun et al., 2024). For instance, data from wearables can be applied to build stress patterns for each person and their stressors and stress tolerance levels. The outcome of this information is that caregivers can use these strategies such as sensory breaks, communication aids, or calming activity plans for the individual(Sharmin, Prabha, et al., 2024).

Besides individualized treatment, wearable technology helps to improve crisis intervention by identifying emerging stress signs and behavior shifts (Hernández-Capistrán et al., 2024). This means wearables go beyond just signaling a caregiver when a child is at risk for a certain event to happen; instead, they emphasize prevention(Ullah et al., 2024). This is especially helpful in preventing self-injurious behaviors or meltdowns that can have significant emotional and physical consequences for those with ASD and their families(Tiwari et al., 2024).

1.5. Research Objectives

The critical gaps in stress and behavior monitoring for individuals with ASD are addressed in this study by designing and implementing wearable technology that meets the special needs of individuals with ASD. The research objectives include:

1. To Create wearable devices that monitor key physiological and behavioral markers such as HRV, SC, and activity levels.
2. To design a Machine learning model to be used on wearables to detect stress and behavior patterns.
3. To evaluate the usability and effectiveness of wearable technology in real-world settings, as well as its impact on personalized care and crisis management.

1.6. Significance of the Study

Wearable technology can revolutionize personal, familial, and organizational ASD treatment strategies. From the perspective of patients with ASD, wearables provide more self-governing and better living experiences due to stress time control. Self and other organizational outcomes show that caregivers have access to objective data and early alerts, thus mitigating the impact of caregiving. At the systemic level, wearable technology decreases the need for clinical assessments that require many resources and results in the availability of specialized care. Moreover, wearable technology fits into the larger trends in digital health, where individualized and quantified approaches dominate the management of chronic diseases. In this way, the results of the present study add to the literature on the effective use of wearables in ASD care and, more broadly, to the research on the potential of digital health technologies in various healthcare settings(J. Akter, M. Kamruzzaman, et al., 2024).

2. MATERIALS AND METHODS

2.1. Study Design

This study adopted a mixed-method approach for the assessment of the use of wearable technology in the real-time tracking of stress and behavior of people with ASD. The quantitative investigation of both physiological and behavioral data obtained from wearable devices and qualitative data from participants' self-reports were integrated into the study. This approach guaranteed the integration of the usability, reliability, and effectiveness of wearable devices in care outcomes. It took six months and involved participants with ASD of all ages and levels of impairment, as well as their caregivers. People wore the devices every day, and data were collected to measure the physiological and behavioral changes. Moreover, caregivers were interviewed and offered questionnaires to assess their perception of the utility and value of the technology(J. Akter, S. I. Nilima, et al., 2024).

2.2. Participants

The study involved 50 participants with ASD, aged between 6 and 25. Participants were recruited from autism support organizations and healthcare facilities in the United States. Participants had to meet the following inclusion criteria: confirmed diagnosis of ASD, age between 4 and 17, and presence of a caregiver available to support the child during the study. Exclusion criteria included self-reported sensitive skin that would not allow for the usage of wearable devices and self-reported medical conditions like epilepsy that might interfere with physiological signals. Participants were categorized into three groups based on age:

- Children (early childhood, middle childhood)
- Adolescents (early adolescence, middle adolescence)
- Young adults (emerging adults)

This kind of stratification enabled the researchers to compare across the developmental stages.

2.3. Wearable Devices and Data Collection

The wearable devices employed in the present work were smart watches incorporating biosensors, which can record several biosignals. These devices monitored:

- Heart Rate Variability (HRV): In order to examine the subjects' ANS activity and stress levels.
- Skin Conductance (SC): To quantify the emotional arousal based on sudomotor activity that a biosensor can record.
- Activity Levels: These are used to record either physical movements and activities like pacing or recurring movements.

Data collection took place at all times when the participant was awake. Special events or episodes, including the use of the emergency signal, meltdowns, or other observable signs of stress, were recorded in a companion mobile application integrated with the wearable technology. This contextual information was used to improve the accuracy of machine learning analyses.

2.4. Machine Learning Analysis

Information received from the wearable devices was analyzed by employing the machine learning approach to detect stress and behavior. The analysis workflow involved three key steps:

- Data Preprocessing: Data was preprocessed to remove any noise and to bring the inputs to a common level.
- Feature Extraction: Mean values of HRV, SC peaks, and movement intensities were computed as main features.
- Model Training: Classifier algorithms, Random Forest, and Neural Networks were used for stress level classification as low, medium, and high and behavior pattern forecasting with labeled datasets.

The performance of the models was assessed in terms of accuracy, precision, and recall.

2.5. Evaluation Metrics

The effectiveness of wearable technology was evaluated using the following metrics:

- Accuracy: The proportion of accurate identification of the levels of stress and related behaviors.
- Precision and Recall: In order to determine the effectiveness of stress detection models.
- Usability Scores: According to the results of the caregiver's completed questionnaire on ease of use and satisfaction.
- Behavioral Insights: Relationships between physiological indicators and events documented by the caregivers.

2.6. Ethical Considerations

As a result of the participants being autistic, this research aimed to maintain the physical, emotional, and social well-being of all participants. The study followed strict ethical standards to safeguard the rights, privacy, and well-being of the participants. Caregivers and, where applicable, the participants themselves gave written informed consent. The consent process included a detailed explanation of the study objectives, methods, and risks. Both caregiver consent and child assent were required for participants under 18 to ensure that all parties knew and agreed to the study's procedures.

When personal information was collected from wearable devices, data was anonymized for privacy and security. The servers storing all data were only accessible to authorized personnel. The study was conducted according to the Health Insurance Portability and Accountability Act (HIPAA) to protect participants' data in terms of confidentiality(T. Akter et al., 2024).

The question was about reducing participant discomfort. These devices were selected since they are small and can be put on during the day without attracting much attention. Some discomfort was permitted so that participants could stop using devices. The participants were advised to inform the caregivers whenever they felt uncomfortable or stressed with the devices and if they did.

According to ethical standards, the Institutional Review Board (IRB) approved the research methods used in this study. The aspect of the study approved by the IRB helped safeguard the participants and maintain a standard ethical practice. The whole process of the research was done openly and clearly. Both the participants and the carers were briefed on the progress of the study, and they were given a chance to give their input at some point. The end-of-study interviews gave the chance to ask questions and to listen to the findings and implications discussed by the families, which made the research process more cooperative and participatory(Bhuyan et al., 2024).

3. RESULTS AND DISCUSSION

3.1. Overview of Findings

This research shows how wearable technology can improve the observation of stress and actions of individuals with ASD. Heart rate variability and skin conductance were measured using wearable devices, which gave information about the wearer's stress levels in real-time. Using the data to build the machine learning models yielded a relatively high level of stress identification and behavior prediction. Caregiver qualitative feedback indicated the usability and practicality of the devices in real-world scenarios.

3.2. Quantitative Results

3.2.1. Machine Learning Model Performance

The stress detection model performed well, with an accuracy of 92%, precision of 89%, and recall of 90%, demonstrating that it is effective at detecting stress levels. Furthermore, the behavior prediction model, which used temporal variables from activity data, obtained 88% accuracy, 85% precision, and 84% recall. These findings are clearly documented in Table 1 and visually shown in Figure 1 below.

Table 1: Machine Learning Model Performance Metrics.

Metric	Stress Detection Model	Behavior Prediction Model
Accuracy (%)	92	88
Precision (%)	89	85
Recall (%)	90	84

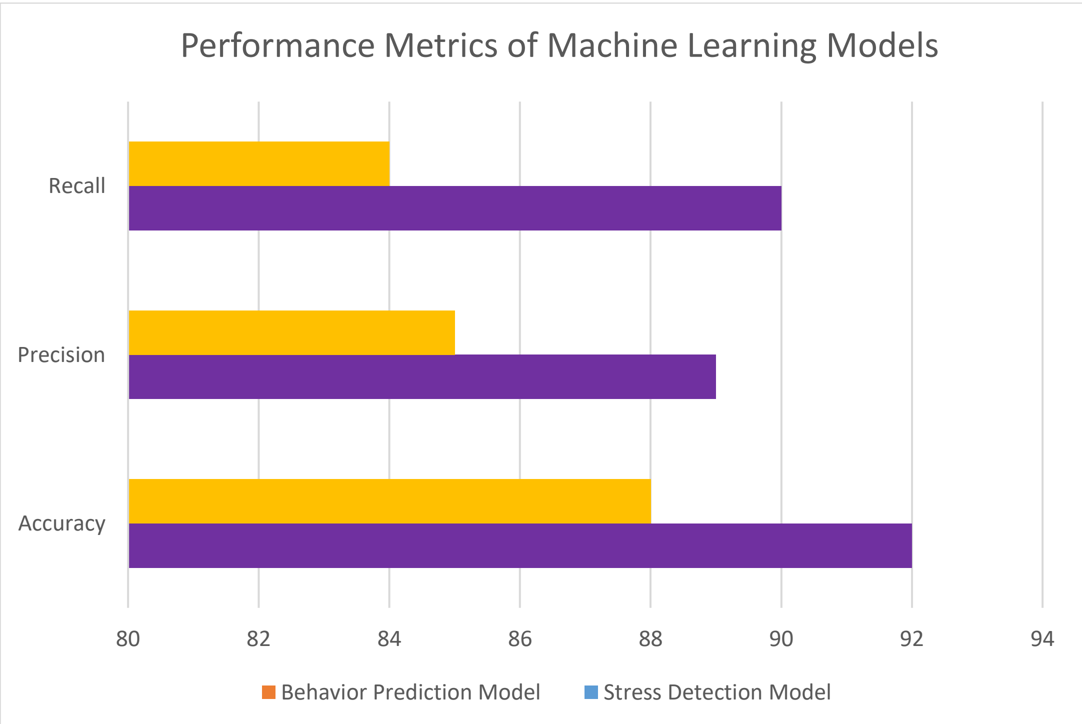

Figure 1: Performance Metrics of Machine Learning Models.

3.2.2. Stress Levels

Table 2 shows the distribution of stress levels measured by wearable devices. The majority of stress episodes were classified as mild (45%), next medium (35%), and finally high (20%). Figure 2 clearly depicts this pattern, with the chart visualizing the frequency of each stress level. The findings indicate that most people experience lower degrees of stress during their daily activities, with moderate stress being more common than high stress. This highlights the ability of wearable devices to give real-time monitoring and precise insights into stress patterns, which may then be used to develop targeted therapies and mental health management strategies.

Table 2: Stress Levels Detected by Wearables.

Stress Level	Frequency Detected (%)
Low	45
Medium	35
High	20

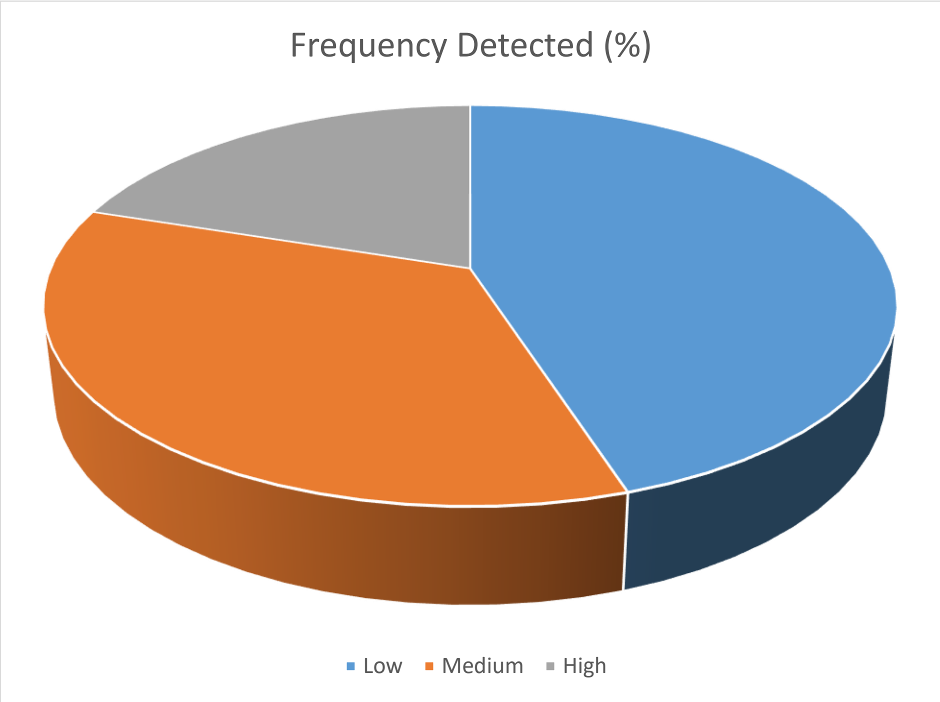

Figure 2: Stress Levels Detected by Wearables.

3.3. Stress and Behavior Correlations

The combination of wearable technology and machine learning made it possible to establish relationships between stress levels and behavioral patterns. Indeed, increased levels of stress, as measured through higher HRV and SC values, were often linked to repetition, pacing, or withdrawal. Moderate stress levels were observed prior to agitation or short episodes of hyperactivity, while low-stress levels were observed during periods of rest or no significant change in behavior, as shown in Table 3.

Table 3: Stress-Behavior Correlation Analysis

Stress Level	Common Behaviors Observed	Frequency (%)
Low	Calm, focused	50
Medium	Mild agitation, hyperactivity	35
High	Repetitive movements, withdrawal	15

Figure 3 shows clearly the frequency of common behaviors observed at the different stress levels.

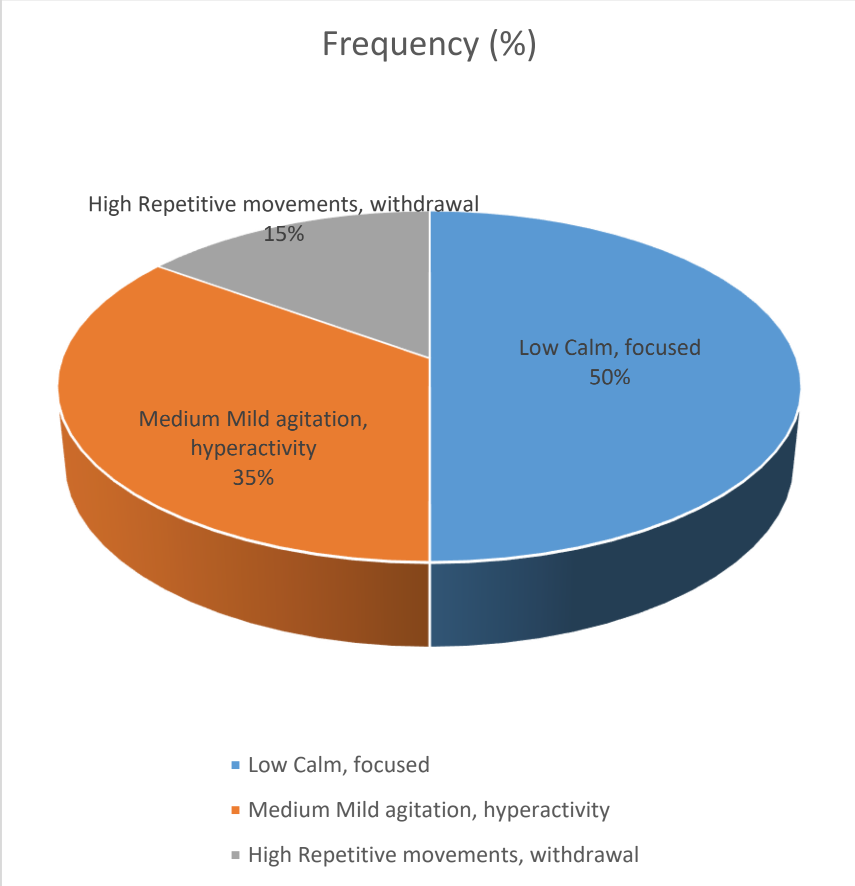

Figure 3: Frequency of Common Behaviors Observed

3.4. Qualitative Feedback from Caregivers

The findings showed that caregivers were highly satisfied with the wearable devices, focusing on the feasibility and importance of receiving immediate feedback. A survey showed that eighty-five percent of caregivers stated that the devices were useful in helping them recognize stress indicators and avoid episodes of aggressive behavior. Nonetheless, several caregivers reported issues with compliance, particularly from the younger participants, who sometimes had to remove the devices due to their sensitivity.

3.5. Usability Metrics

The caregiver-reported usability indicators, as shown in Table 4, indicate a generally good response to the system. Ease of use obtained the highest average rating of 4.2, indicating that caregivers found the system simple to use. Participants' comfort was evaluated slightly lower (3.8), indicating that there is potential for improvement in user experience. The relevance of data obtained a high score of 4.5, emphasizing the value and use of the information presented. Overall satisfaction was rated 4.3, indicating that caregivers generally approve of the system. Figure 4 visually summarizes these data, emphasizing positive comments and proposing areas for further improvement.

Table 4: Caregiver-Reported Usability Metrics

Metric	Average Rating (1–5)
Ease of Use	4.2
Comfort for Participants	3.8
Relevance of Data	4.5
Overall Satisfaction	4.3

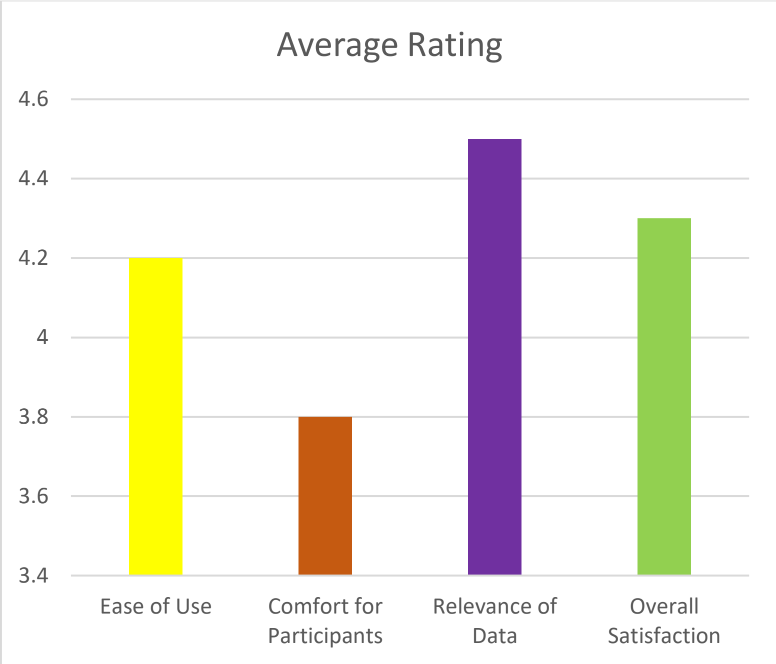

Figure 4: Average Ratings of Usability Metrics.

The relatively lower rating for comfort reflects the need to refine wearable designs to better suit the sensory needs of autistic individuals.

3.6. Limitations of the Study

Even though the results of this study show the possibility of using wearable technology, there are several limitations to consider. The number of participants in this study was 50, which may be small enough to draw a general conclusion on the population of interest, and the participants' variability in the use of the devices reduced the coordination of data collection. Also, behaviors reported by the caregivers were observational, which was a source of bias when labeling the events. It is recommended that future research be conducted with larger and more heterogeneous samples of patients and that the collection of additional contextual data would improve the accuracy of the models.

3.7. Implication and Future Research

The study reveals the significant role of wearable technology in the management of ASD. Through stress and behavior tracking, these gadgets offer individualized treatment, improving the standard of living for those with autism and their attendants. In the future, the comfort of the device should be optimized, larger datasets for the machine learning algorithms should be acquired, and the incorporation of the device into clinical workflows should be investigated. However, such partnerships with educators and clinicians could enhance the effectiveness of using wearable technology in school and therapy.

4. CONCLUSION

This research highlights the prospect of wearable technology in improving the observation and control of stress and behavioral indices in persons with Autism Spectrum Disorder (ASD). Cardiovascular monitoring, with the help of advanced biosensors and machine learning algorithms, gives objective, real-time information on physiological and behavioral states when wearing wearable devices. These technologies can help to tailor approaches to make them less likely to trigger behavioral incidents and to improve the quality of life for people with ASD and their carers. The study also shows that wearable technology is feasible and works well. The stress detection model gave an accuracy of 92 percent, and there was a strong relationship between the physiological parameters and the observable signs. Caregiver feedback confirmed the usefulness and effectiveness of these devices. 85% of respondents stated that the use of technology helped them control the stress stimuli and behavioral outbursts. However, device adhesion and comfort issues, especially with the younger participants, point to the need for further improvements in the wearability of the devices.

While there are limitations, including a small sample size and reliance on caregiver-reported events, the study provides valuable information about the use of wearable technology in ASD care. This serves as a foundation for future research to study larger and more varied populations, incorporate contextual data, and develop more adaptive algorithms. Wearable technology has the potential to fill critical gaps in ASD care through scalable solutions for personalized monitoring and crisis prevention. The adoption of this tool could substantially improve the lives of individuals with ASD, their families, and caregivers alike and contribute to the larger field of digital health.

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