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Full Length Article

Continuous Well-Being assessment and actionable feedback using explainable regression for Edge-Enabled wearable devices

Sheikh Muhammad Saqib [a], Tehseen Mazhar [b,k,*], Amal Al-Rasheed [c], Muhammad Usman Tariq [d], Muhammad Amir Khan [e,*], Tariq Shahzad [f], Sunawar Khan [b], Habib Hamam [g,h,i,j]

[a] Department of Computing and Information Technology, Gomal University, Dera Ismail Khan 29050, Pakistan
[b] School of Computer Science, National College of Business Administration and Economics, Lahore 54000, Pakistan
[c] Department of Information Systems, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia
[d] Department of Marketing, Operations, and Information Systems, College of Business, Abu Dhabi University, Abu Dhabi, United Arab Emirates
[e] School of Computing Sciences, Faculty of Computer Science and Mathematics, Universiti Teknologi Mara, Shah Alam, 40450 Selangor, Malaysia
[f] Department of Computer Engineering, COMSATS University Islamabad, Sahiwal Campus, Sahiwal 57000, Pakistan
[g] Faculty of Engineering, Uni de Moncton, Moncton, NB E1A3E9, Canada
[h] School of Electrical Engineering, University of Johannesburg, Johannesburg 2006, South Africa
[i] International Institute of Technology and Management (IITG), Av. Grandes Ecoles, Libreville BP 1989, Gabon
[j] Bridges for Academic Excellence - Spectrum, Tunis, Centre-ville, Tunisia
[k] Department of Computer Science and Information Technology, School Education Department, Government of Punjab, Layyah 31200, Pakistan

A R T I C L E I N F O

Keywords:
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A B S T R A C T

As the utilization of wearable devices in health monitoring continues to expand, there is a pressing need for intelligent system designs that can not only collect physiological data but also transform it into results that are comprehensible, meaningful, and practical. The application of current models in real-world digital well-being measurement is limited by their inability to provide continuous feedback or personalized recommendations. In the paper, we propose a regression-based model that is both technically stable and interpretable, and that is used to estimate the well-being score using data from ubiquitous sensors. The system employs a Ridge Regression model with counterfactual reasoning to provide high-fidelity score predictions ($R^2 = 0.9996$, MSE = 0.0275, RMSE = 0.166), as well as human-interpretable behavioral advice. The well-being score is expected to fall within the range of 34 to 80, with a higher score indicating exceptional well-being and a lower value indicating a deterioration in physical or mental status. One of the decision statuses is assigned to each result. Scores of 75 and more are reasons to continue the same behaviour and strengthen the positive routines, and scores of 40 and less are signs of critical levels of well-being. It is better to take some rest, practice mindfulness, or find clinical support. This interpretability degree will allow real-time and personalized decision support to both the user and the linked wearable systems. The proposed framework will be designed to operate in wearable technologies with minimal power and be deployed on-device, in contrast to other literature works that are either not transparent or do not produce actionable feedback. In contrast to other previous works that were not transparent or rationally based, this one involves precise predictions, interpretability, and personalized guidelines. It offers a comprehensive solution for smart health monitoring by converting sensor data into meaningful scores and proactive well-being management recommendations.

* Corresponding authors.
E-mail addresses: saqibsheikh4@gu.edu.pk (S.M. Saqib), tehseenmazhar719@gmail.com (T. Mazhar), aaalrasheed@pnu.edu.sa (A. Al-Rasheed), Muhammad.kazi@adu.ac.ae (M.U. Tariq), amirkhan@uitm.edu.my (M.A. Khan), tariq@cuisahiwal.edu.pk (T. Shahzad), sunawarkhan@gmail.com (S. Khan), Habib.Hamam@umoncton.ca (H. Hamam).

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1. Introduction

1.1. Context and motivation

The health of individuals can be improved incrementally by combining sensor data from wearable devices with conventional risk factors and Artificial Intelligence (AI) [1–3]. The field of personalized healthcare, ubiquitous computing, and real-time human–computer interaction [4,5] is being revolutionized by the integration of wearable electronics and AI technologies, particularly Machine Learning (ML) and Deep Learning (DL). Wearable devices, such as smartwatches, fitness monitors, health patches, and glasses with augmented reality, have become an integral part of daily life. This allows for the continuous collection of environmental data, behavioral trends, and physiological data. Due to the automated interpretation of multimodal data streams, these tools offer both users and healthcare personnel timely and responsive health information, facilitated by a series of sensors and intelligent functions [6].

In healthcare contexts, wearable electronics are being used to continuously monitor key health parameters, including heart rate, sleep patterns, physical activity, and stress levels. The associated change in proactive surveillance contributes to the earlier diagnosis and management of chronic diseases, as well as the potential to provide real-time feedback on lifestyle choices. Their significance is further underscored in rural and underserved regions, where the absence of healthcare facilities introduces significant disparities in the diagnosis and treatment of the issues. Wearables offer a scalable and cost-effective solution by increasing access to health care and allowing individuals to monitor and manage their health without being physically dependent on hospitals and clinics. As an example, deep learning models that are based on intracranial electroencephalogram (iEEG) data have been proposed as a method of automatically predicting epileptic attacks, even when the individual is not present at the hospital or clinic [7].

A new concern in the field of wearable and digital health is digital well-being, which refers to the role of digital technologies in human interaction and their impact on individuals' mental, emotional, and physical well-being [8]. Digital well-being is a metric that evaluates the behavior of smartphone use, in contrast to conventional health metrics such as screen time, app use, social media use, notifications, and sleep patterns. These digital footprints are directly correlated with cognitive performance, affective stability, anxiety, and productivity. Consequently, digital well-being is a significant but underappreciated aspect of the broader health issue. The use of AI-powered peripheral devices to continuously monitor digital well-being not only increases awareness but also enables the early detection of minor behavioral deviations before they cause mental distress or health issues. This is especially true in technologically advanced societies, where the issue of digital stress and screen time is a significant concern.

The majority of the current AI-based approaches to peripheral data have two significant limitations: a lack of interpretability and the absence of personalized and actionable recommendations, despite the development of such solutions. The current models are more prone to classification (e.g., tension vs. no stress) and are not particularly transparent about the prediction process, often failing to provide real-time guidance that the user can follow. User confidence, model utility, and long-term health performance are all compromised by these vulnerabilities.

Furthermore, there is a significant paucity of lightweight, real-time solutions that can be directly delivered to edge devices, such as wearables, in underserved contexts. An explainable, regression-based, and actionable framework that can operate on low-power hardware would thereby constitute a substantial void in the digital health technology ecosystem.

1.2. Main objective

This study aims to develop an explainable, regression-based machine learning framework that predicts digital well-being scores from wearable sensor data and transforms these predictions into real-time, user-specific behavioral guidance and device-level recommendations.

The core idea is to go beyond opaque classification models by offering a continuous well-being score, explainable through LIME, and further enhanced by counterfactual reasoning. This enables users to understand not only their current status, but also how they can improve or maintain it—empowering them to make better decisions and adopt healthier digital habits.

1.3. Key contributions

This work makes the following key contributions:

- A transparent Ridge Regression model is trained on real-world behavioral data to predict digital well-being scores with high accuracy ($R^2 = 0.9996$, RMSE = 0.166), offering fine-grained, interpretable outputs.
- Integration of Explainable AI techniques, including LIME visualizations, allows users to understand how individual features (e.g., anxiety level, sleep hours) impact their score.
- Counterfactual analysis is employed to determine what specific changes would improve or worsen the user's well-being score, offering personalized behavioral advice.
- The framework provides two levels of actionability: (1) recommendations for the user (e.g., reduce app switching), and (2) adaptive suggestions for the wearable device itself (e.g., enable DND mode).
- Unlike prior work, the proposed system is designed for low-power, edge deployment, making it suitable for real-time health monitoring in wearable devices, especially in remote or underserved environments.

2. Literature review

2.1. Current research

To detect anomalies in mental health, Explainable Anomaly Detection of Depression and Anxiety [9] employs an LSTM auto-encoder with SHAP-based interpretability. The model flags anomalies rather than providing behavior-level adjustments to the user, despite having an F1 score of approximately 0.80. By proposing the prognosis of a continuous well-being score and offering visual explanations with concrete suggestions for behavioural change, this model has been developed.

One example of a Wearable Device Dataset on mental health assessment using laser Doppler and Spectroscopy [10] utilizes LightGBM classifiers to identify stress and anxiety by analyzing physiological measurements. The model is a classifier that lacks a well-being score and actionable decisions, despite having achieved an ROC AUC of approximately 0.72. The proposed model enhances this by converting sensor data into a continuous, interpretable well-being score and providing context-based recommendations.

Identifying fatigue and overall health. The literature on burnout biomarkers is summarized in Wearable Technologies [11], but predictive models that are comprehensible and beneficial to users as guidance have not been developed. The proposed model addresses this void by offering a transparent regression model that incorporates custom-made behavioral advice and thresholds.

The systematic analysis of the function that explainable AI plays in wearable data is the primary focus of the review of Explainability in Wearable Analytics [12]. The research indicates a substantial lack of transparency, and there are few solutions available to assist in making practical decisions. Ridge regression and counterfactual logic will be incorporated into the proposed model to provide recommendations at the device and human levels, thereby addressing this vulnerability.

The PhysioFormer: Explainable Multimodal Affective State Prediction [13] model is a highly accurate approach that integrates symbolic regression with the prediction of mood states based on multimodal physiological information, with a precision of over 99 %. However, it is limited to classification and is unable to convert predictions into user actions. The proposed model enhances the continuous regression approach by integrating actionable insights and behavioral recommendations.

Accelerometer Foundation Models of Health [14] presents foundation models that have been refined through the use of accelerometry and a variety of health outcomes. It is technically innovative, but it is not concerned with well-being scoring or explainable decision logic. The proposed model employs the same data, but it transforms it into a score-oriented system that is more practical.

TEANet: Wearable Stress Monitoring with Deep Autoencoders [15] is a study that employs a deep autoencoder to accurately capture stress based on BVP signals, achieving an accuracy of 93–97 %. Despite its high-frequency detection capabilities, it lacks a well-being scoring mechanism and actionable insights. The proposed model converts the detection results into a scoring framework for recommendations that is based on both human and wearable data.

In the Digital Device Use and Well-Being Study Protocol [16], a study is described that establishes a connection between device use and mental health by utilizing self-reported surveys and sensor data. However, no model is proposed. The proposed model is capable of generating interpretable regression models that can offer real-time feedback and practical recommendations by utilizing analogous input information.

The review article "Integration of AI/ML in Wearable Health Devices: Paradigm Shift" [17] discusses the integration of AI/ML in wearable health devices. However, it lacks specific assessment models and decision-support mechanisms. The proposed model addresses this lacuna by providing users and the device with an integrated regression-based score, status classification, and dynamic propositions.

The article "Smartwatches in Stress Management, Mental Health, and Well-Being: A Systematic Review" is A systematic review of the current literature on the use of wearable-based monitors to measure stress and well-being, as represented in [18]. Even though it summarizes the findings of numerous studies, it does not presuppose any interpretable decision logic or interventions at the feature level. The proposed model augments this by employing counterfactual recommendations to categorize the status, in addition to utilizing regression to assess well-being. This approach renders the system more comprehensible and feasible.

Recent research also highlights the growing potential of edge-enabled wearables and low-power ML models for continuous well-being assessment and feedback in digital health. Ghadi et al. [2] demonstrated that integrating wearable technology with AI methods—such as federated learning, deep learning for noise filtering, and blockchain for secure data transmission—can significantly enhance remote patient care by addressing challenges like data overload, privacy concerns, and EHR integration. Their structured roadmap offers practical AI-driven solutions for personalized interventions, real-time anomaly detection, and scalable, trustworthy healthcare delivery. Similarly, Ali et al. [19] proposed an edge-based IoT framework that enables real-time anomaly detection for elderly care using non-wearable sensors, demonstrating how local data processing improves responsiveness, minimizes privacy risks, and facilitates early interventions through the use of isolation forests and LSTM networks. Vegesna [20] evaluated CNNs, RNNs, Random Forests, and hybrid models for real-time mental health monitoring using wearable sensors, finding that CNNs are particularly effective for multi-dimensional time-series data. In contrast, GAN-based data augmentation can address the lack of labeled data—highlighting the importance of model efficiency, adaptability, and scalability for continuous mental health surveillance.

In terms of methodological alignment, Khan et al. [21] introduced a transparent classification framework called ExplainableClassifier that integrates LIME, SHAP, and counterfactual reasoning to reclassify ambiguous eligibility categories in clean alternative fuel vehicle datasets. Their emphasis on interpretability, robustness, and policy-oriented insight demonstrates the power of XAI for actionable classification and reclassification—an approach mirrored in the proposed model's use of counterfactuals for personalized behavioral feedback.

Additionally, Umar et al. [22] proposed an energy-efficient deep learning-based intrusion detection system optimized for edge devices using knowledge distillation and model quantization (DNN-KDQ). Although focused on cybersecurity, their model's high accuracy, reduced inference time, and dramatically compressed size confirm the feasibility of real-time, low-latency ML deployment in resource-constrained environments—an essential requirement for the on-device execution of digital well-being models such as the one presented in this study.

Wearable AI systems are now being explored not only for detection but also for real-time decision-making. Mahajan et al. [23] demonstrated the integration of wearable AI with clinical workflows to enhance patient safety by delivering personalized, real-time guidance. Such systems enable proactive care across diverse medical settings—from tracking infectious diseases to AI-assisted surgery—pointing toward the future of wearable health companions with embedded intelligence. However, effective clinical deployment requires transparency and trust in model outputs, especially among healthcare professionals. Wysocki et al. [24] revealed that while healthcare providers appreciate explainable models, poor-quality explanations can lead to automation bias and over-reliance, particularly when explanations fail to reflect model uncertainty or contextual limitations. This insight suggests that explanations must be both informative and pragmatically embedded in clinical workflows to avoid unintended harm.

To address these communication gaps, Joyce et al. [25] introduced the TIFU (Transparency and Interpretability For Understandability) framework, advocating for human-centric definitions of explainability in mental health contexts, where data often exhibit probabilistic and multifactorial relationships. Their work emphasizes the need for AI systems whose logic, assumptions, and outputs are not only accurate but also comprehensible, ensuring adoption in psychiatry and related disciplines. Complementing this, Nasarian et al. [26] provided a systematic review of interpretable ML and XAI methods in clinical decision support systems (CDSS), proposing a three-tier interpretability framework (pre-, in-, and post-processing) and outlining a roadmap for bridging communication gaps between AI tools and clinicians. They underscore the risks of mistrust and underuse when interpretability is not adequately addressed in the system design.

Collectively, these studies underscore the importance of combining edge intelligence, low-power learning models, and meaningful interpretability for real-time, user-centered health monitoring. They also reveal the critical role of counterfactual and causal reasoning in helping users and clinicians understand how and why predictions change based on behavior or system input. The proposed model aligns with these advances by integrating explainable Ridge regression with LIME visualization and counterfactual analysis, enabling transparent, efficient, and personalized digital well-being recommendations suitable for deployment on wearable devices.

2.2. Research Gap.

Despite significant advancements in wearable-based digital health systems, existing studies exhibit critical limitations that hinder their real-world applicability and user trust. Most current models are designed as classification frameworks (e.g., stress/no stress or anomaly detection), which do not provide a continuous measure of well-being or explain how specific user behaviors influence outcomes. This lack of granularity and interpretability makes it challenging for users to translate predictions into actionable lifestyle adjustments.

Another limitation is the absence of personalized feedback and counterfactual reasoning. While studies employing Explainable AI (e.g., SHAP, LIME) offer insight into feature importance, they rarely extend to "what-if" analyses that guide users on how modifying factors—such as reducing screen time or improving sleep patterns—can directly enhance their well-being score. This omission reduces the practicality of existing models for behavior-driven decision-making.

Additionally, most prior work is not optimized for edge-enabled wearable deployment. Many AI models require significant computational resources or cloud-based processing, which raises privacy concerns, increases latency, and limits real-time responsiveness. Studies like [2] and [22] demonstrate that low-power, edge-compatible solutions are feasible. Still, these approaches have not yet been fully exploited for digital well-being scoring combined with explainability and actionable guidance.

Finally, there is a lack of integrated frameworks that combine prediction, explainability, and intervention. Existing reviews [11,12], and [18] highlight that most wearable health systems stop at data monitoring or anomaly detection without offering comprehensive, interpretable decision support. There is a need for systems that not only achieve high predictive accuracy but also deliver transparent, user-specific behavioral recommendations and adapt dynamically to changing patterns in real time.

3. Proposed methodology for AI-Driven digital well-being

The article describes a novel machine learning model that can predict and enhance an individual's online well-being. The proposed system integrates predictive modeling with actionable and personalized insights, as illustrated in Fig. 1. The methodology can be divided into the following essential stages.

3.1. Data Acquisition and model development

The system is founded on a database of health and behavioral metrics that were acquired from Kaggle [27]. These metrics are categorized as independent and dependent features. The independent features (sensor data) are the variables that the model employs to make predictions. They include daily_screen_time_min, num_app_switches, sleep_hours, notification_count, social_media_time_min, focus_score, mood_score, and anxiety_level. The dependent feature (predicted score) is the target variable for the model, the digital_wellbeing_score, which is the outcome that the model aims to predict Based on the digital well-being score, the target variable, the model is anticipated to forecast the value. The score ranges from a critical well-being alert (34.6) to excellent digital well-being (80.8). Table 1 illustrates the data and values that were employed to train the model.

3.2. Model training and Evaluation

3.2.1. Ridge regression model

The Ridge Regression model is suggested for application in this study due to its transparency and capacity to forecast the digital well-being score. To achieve optimal performance, the model's parameters were optimized to include alpha = 1.0, test_size = 0.5, train_size = 0.5, and random-state = 42.

The model's performance was rigorously evaluated using test data that was obtained subsequent to the training. Table 2 indicates that the model achieved a high accuracy and low error value, with an R2 score of approximately 0.9995 and an RMSE of 0.166. This is visually demonstrated in Fig. 2, where the actual and predicted well-being scores exhibit a robust correlation. A well-performing model is also illustrated in Fig. 3 (residuals distribution), where the error distribution is approximately zero.

Fig. 3 illustrates the Ridge Regression model's predictive capacity in digital well-being scores. On the test dataset, the x-axis of the diagram represents the actual values of the well-being of people x. In contrast, the y-axis represents the predicted value of the well-being of people x as predicted by the model. The Ideal Fit, represented by the black diagonal line, represents a situation in which the real and forecasted values are equivalent (i.e., y = x). The purple scatter points are individual predictions, and their proximity to the Ideal Fit line indicates a strong correlation between actual and predicted scores. This clustering confirms that this model is capable of producing high-quality predictions with minimal errors, as evidenced by the reported values of low RMSE and high R 2. The Ridge Regression model is robust in the estimation of well-being scores, as evidenced by the plot.

3.2.2. Explainable AI (XAI) analysis

This methodology will incorporate Explainable AI (XAI) analysis to establish transparency and acquire user trust, which is a consequence of the black-box nature of numerous machine learning models. The LIME (Local Interpretable Model-agnostic Explanations) framework is employed to elucidate the predictions of individual instances.

The LIME analysis of two data records (Record 0 and Record 200) is illustrated in Figs. 5 and 6. To inform users of the reasons for their

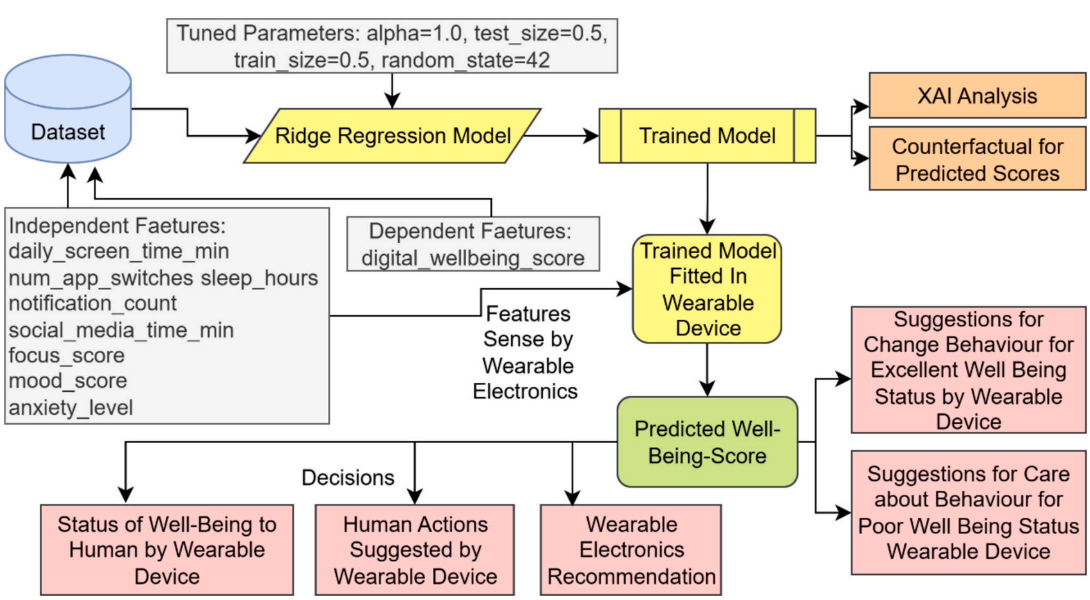

Fig. 1. Proposed Work for Suggestions for Human from Trained Model from Sensor Data.

Table 1
Sample Dataset for Understanding Features and Values.

daily_screen_time_min	num_app_switches	sleep_hours	notification_count	social_media_time_min	focus_score	mood_score	anxiety_level	digital_wellbeing_score
389.8	53	5.9	89	133.2	6.8	8.9	10	44.8
351.7	52	7.2	79	109.5	5.5	9.4	10	43.6
398.9	39	8	108	84.7	6.7	9.4	9.4	52.6
451.4	44	6.5	78	88.9	6	9.4	5.1	58.4
346	43	6.9	35	78.8	8.2	9.4	8	59.7
346	38	8.5	111	82.6	7.4	9.9	7.8	61.6
454.8	40	6.8	57	117	7.3	9.2	10	49.7
406	57	9.6	63	87.8	7.6	9.3	9.8	59.9
331.8	42	7.2	65	150.7	6.9	10	8.5	53.6
392.6	63	4.4	114	186.9	7.2	7.6	10	41.8

Table 2
Proposed Model's Performance Results on Test data.

Metric	Value
R^2 Score (Accuracy)	0.9995508742083273
Mean Squared Error (MSE)	0.027545093197652522
Root Mean Squared Error (RMSE)	0.16596714493432888
Mean Absolute Error (MAE)	0.13439927381797437
Mean Absolute Percentage Error (MAPE)	0.0026503659500782015
Median Absolute Error	0.10917251773426528
Max Error	0.44996716787888147
Explained Variance Score	0.9995582950810852

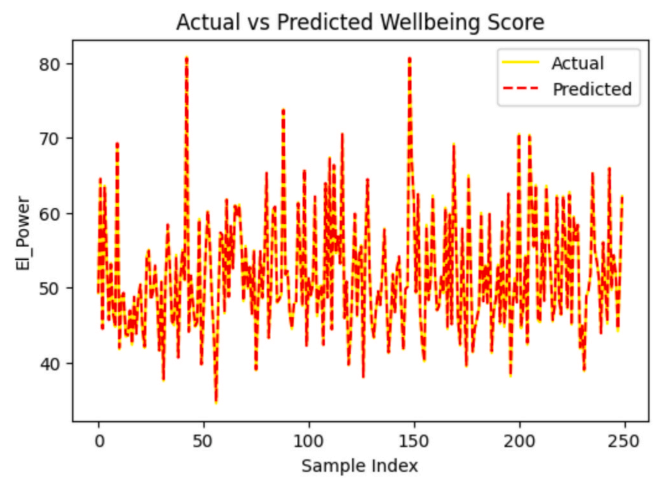

Fig. 2. Actual vs Predicted Well-being Score.

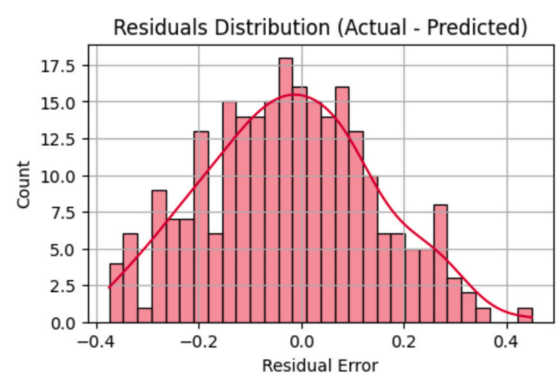

Fig. 3. Residuals Distribution (Actual Well-being Score – Predicted Well-being Score).

scores, these images specify the specific factors that either positively or negatively affect the estimated digital well-being score. For instance, Fig. 4 illustrates that the final score is positively influenced by the number of sleep hours, while anxiety levels have a negative influence on the final score.

3.3. Counterfactual reasoning and personalized recommendations

Counterfactual analysis is one of the most significant innovative aspects of this work. This method illustrates the necessary adjustments that a user must make to achieve a distinct well-being score. The system is capable of automatically generating these human action suggestions and providing recommendations to the wearable device.

In the system, there are several instances of counterfactual analysis. The score can be maximized to 80 by conducting a counterfactual analysis on a user with an anticipated score of 58 (Record 33). They are

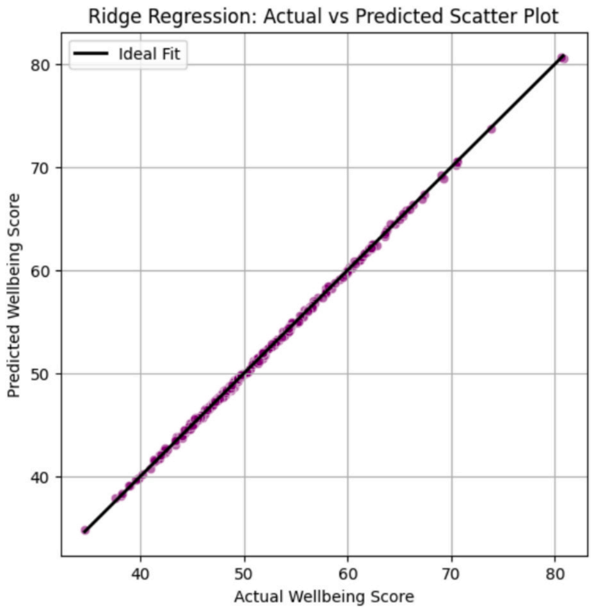

Fig. 4. Ridge Regression: Actual vs Predicted Scatter Plot.

most likely to decrease their anxiety level to 1.5 and the number of applications they switch to 45 per day by achieving a well-being score of over 80. The same is depicted in Fig. 7 and Table 3.

On the other hand, Table 4 and Fig. 8 shows the process of obtaining a low score (34) out of an initial score of 58. It means that the main behavioral changes would be to reduce the number of hours spent sleeping to 3.7 and focus score to 5.6.

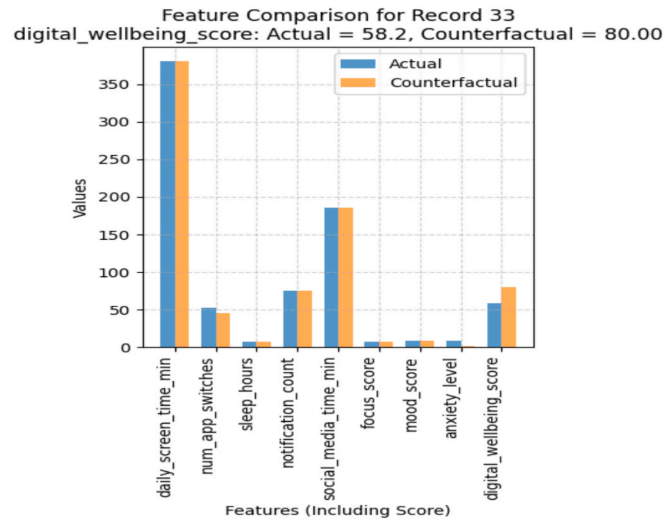

Fig. 7. Visual Representation of Change of Features for Score 58 to 80 for Record-33.

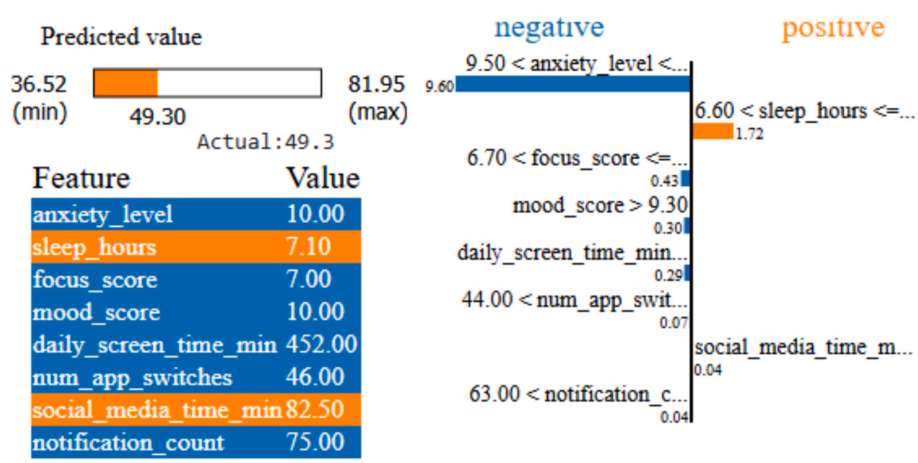

Fig. 5. Lime Analysis for Record-0 for Prediction of Digital Well-being Score.

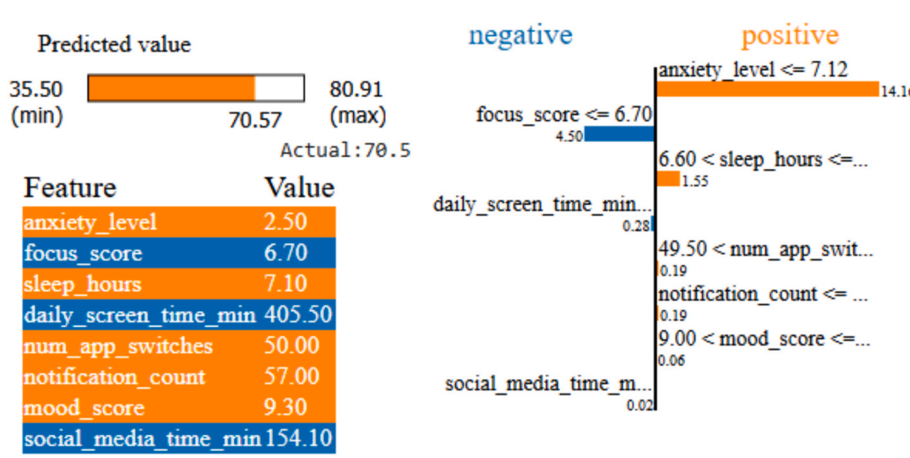

Fig. 6. Lime Analysis for Record-200 for Prediction of Digital Well-being Score.

Table 3
Turn Predicted Score 58 to 80 with Feature Modification for Record-33.

Feature	Actual Record	Modified Features
daily_screen_time_min	380.5	380.5
num_app_switches	52	45
sleep_hours	7.9	7.9
notification_count	75	75
social_media_time_min	185.5	185.5
focus_score	7.8	7.8
mood_score	8.3	8.3
anxiety_level	8.8	1.5
digital_wellbeing_score	58.0	80.295441

Table 4
Turn Predicted Score 58 to the nearest 34 with Feature Modification for Record-33.

Feature	Actual Value	Modified Value
daily_screen_time_min	380.5	380.5
num_app_switches	52	52
sleep_hours	7.9	3.7
notification_count	75	75
social_media_time_min	185.5	185.5
focus_score	7.8	5.6
mood_score	8.3	8.3
anxiety_level	8.8	8.6
digital_wellbeing_score	58.0	37.851101

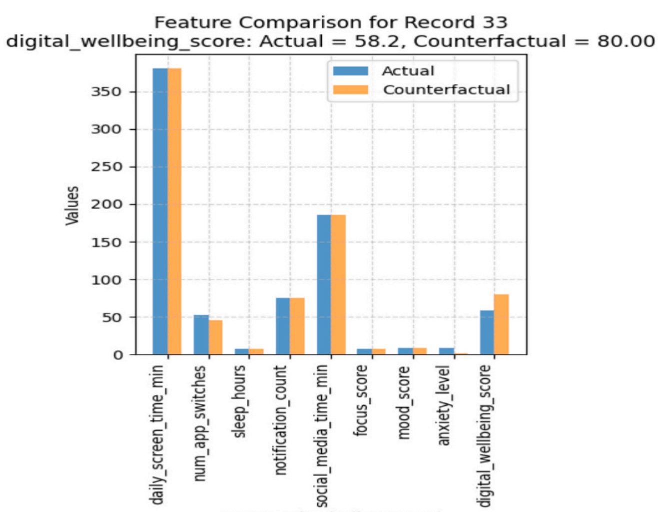

Fig. 8. Visual Representation of Change of Features for Score 58 to 37 for Record-33.

In the case of a user with an outstanding score of 81 (Record 148), the counterfactual illustrates the way in which an alteration of behavior will decrease the score to a critical point. Table 5 and Fig. 9 would indicate that a score of around 35 would be obtained by reducing the sleep_hours to 3.6 and increasing the anxiety_level to 9.6.

Table 5
Turn Predicted Score 81 to 35 with Feature Modification for Record-148.

Feature	Actual Value	Modified Value
daily_screen_time_min	356.399994	356.4
num_app_switches	42	40
sleep_hours	8.8	3.6
notification_count	88	88
social_media_time_min	121.099998	121.1
focus_score	7.5	5.7
mood_score	8.4	8.6
anxiety_level	1.9	9.6
digital_wellbeing_score	81.0	34.983662

Lastly, with a critical score of 35 (Record 56), Table 6 and Fig. 10 reveal that by raising sleep_hours to 9.8 and focus_score to 8.7, along with other minor modifications, it is possible to have a user score significantly higher than 80. Table 7. shows the Proposed Human Action and Wearable Electronics Recommendations based on Predicted Well-being Scores.

These counterfactual conditions are what allow the system to provide the user with dynamic and personalized advice, such as reducing screen time or improving sleep habits, and to activate device features, such as a do-not-disturb mode.

3.4. Real-Time intervention and proactive healthcare

Ultimately, it is anticipated that this trained, comprehensible model will be integrated into a wearable device. This will enable the real-time sensing of data, the prediction of the well-being score, and the automatic generation of recommendations for the actions and devices that humans should use. This framework establishes a foundation for proactive and personalised health, particularly in remote regions where ubiquitous electronics may function as indispensable health companions.

Fig. 8 illustrates a comprehensive strategy for integrating real-time well-being predictions into actionable results, thereby advancing the concept of proactive and personalized healthcare. Interventions are implemented promptly, as individuals receive personalized Human Action Recommendations and Wearable Electronics Recommendations in accordance with the anticipated well-being score of the model. The system issues a Critical Well-being Alert when the user's score is less than 40. This initiates the following actions: direct mental health assistance, a significant reduction in screen time, and mindfulness exercises. In accordance with this, it is advised that wearable devices be used to transmit an emergency support message and monitor anxiety levels. The actions in the Moderate Concern (40–59) category include limiting the use of apps, reducing notifications, and engaging in moderate physical activity.

Additionally, wearables provide a well-being summary, reminding the user of the importance of maintaining a digital balance. In the range

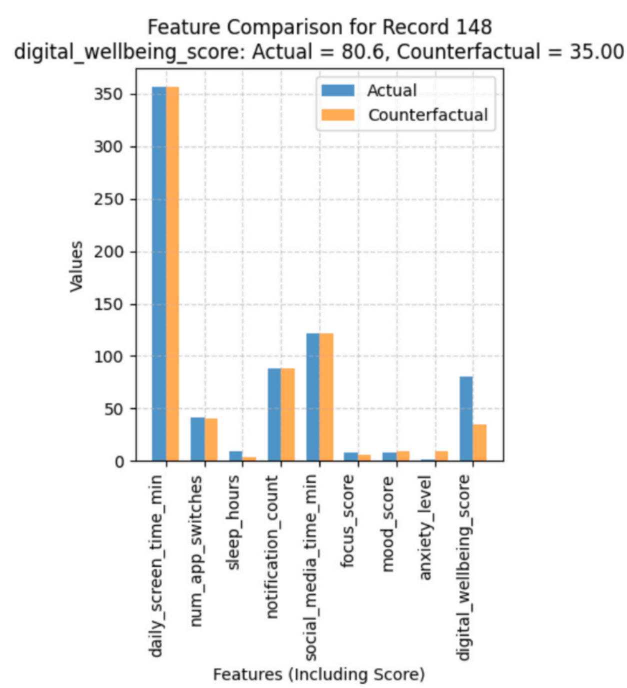

Fig. 9. Visual Representation of Change of Features for Score 81 to 35 for Record-148.

Table 6
Turn Predicted Score 35 to 80 with Feature Modification for Record-56.

Feature	Actual Value	Modified Value
daily_screen_time_min	391.299988	438.3
num_app_switches	65	65
sleep_hours	3.7	9.8
notification_count	105	105
social_media_time_min	158.199997	168.2
focus_score	5.9	8.7
mood_score	8.0	8.0
anxiety_level	10.0	4.6
digital_wellbeing_score	35.0	80.178070

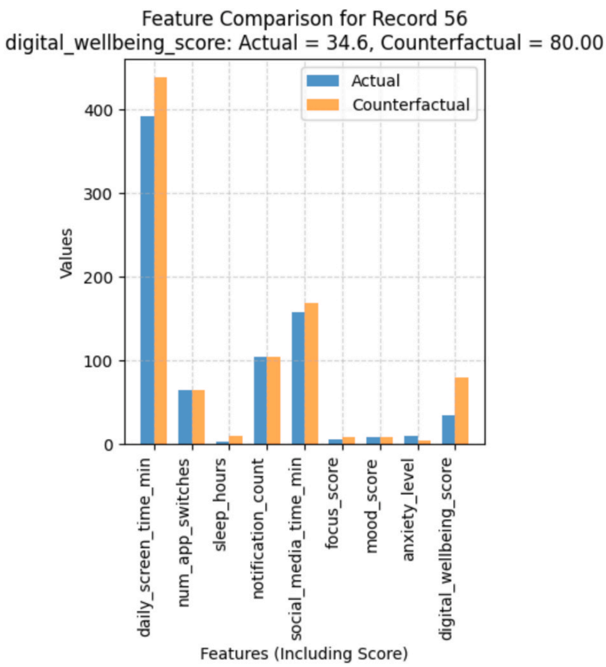

Fig. 10. Visual Representation of Change of Features for Score 35 to 81 for Record-56.

of 60 to 74, which are known as "Stable But Monitor" scores, it is advised that users maintain their current habits. Wearables can assist in this endeavor by providing health monitoring and inspirational notifications. Finally, scores of 75 or higher indicate an Excellent Digital Well-being, which encourages users to maintain and disseminate their healthy habits. Wearable devices can also offer positive reinforcement. Smart, responsive digital health systems are preconditioned by this framework, which empowers individuals, particularly in remote or underserved areas.

4. Results and Discussion

The proposed model's automated predictive functions and practical application were demonstrated through the taking of photographs of the Python-based system's output. The dynamics of the model, as it processes input data and presents real-time decisions on various case studies, are illustrated by these graphical models.

4.1. Automatic decisions by proposed work embedded in a wearable device for case study Record 56

Detailed visual representations of the entire dynamic in action for a specific user are provided in Fig. 11. It demonstrates the system's ability to provide both short-term intervention and a long-term course of action by integrating sensor data into actionable recommendations.

Table 7
Proposed Human Action and Wearable Electronics Recommendations based on Predicted Well-being Scores.

Score Range	Status	Human Action Recommendations	Wearable Electronics Recommendations
< 40	Critical Well-being Alert	– Mental health care should be offered immediately- Minimize screen time- Clean off social media- Mindfulness or breathing exercises.	– Take more reminders to sleep hygiene- Emergency support notification activated in case of a connection- Turn on relaxation or meditation mode- Pay attention to the indicators of anxiety.
40 – 59	□ Moderate Concern	– Examine everyday stressors- Minimize the act of switching apps- Turn notifications off or put on DND- perform light physical activity or spend time outside.	As you can see, we have covered all of the essentials of a well-balanced yet health-aware mind.<|human|>As you have seen, we have already discussed all the keys to a healthy yet balanced mind.
60 – 74	□ Stable But Monitor	– Have healthy screen time- Keep engaging in focus-enhancing activities- Maintain a screen time/ real-life interaction balance.	– Uninterrupted monitoring- Rewarding good behaviors with motivation notices- Encourage regular breaks to maintain good health.
≥ 75	□ Excellent Digital Well-being	– Keep up with digital habits- Lead by example by taking classes together- Check in with oneself on a regular basis.	– Maintain existing tracking habits- Express good patterns- Fete regularity through minor positive feedback.

4.1.1. Inputs from sensors

The sensors start with the process inputs. This part at the top of the figure shows a snapshot of the data of a user that was recorded by a wearable device on a particular day, known as Record 56. The data contains the most critical metrics, including daily_screen_time_min (391.2), the number_app_switches (65), sleep_hours (3.7), notification_count (105), and other well-being indicator attributes. The values are the raw and objective, behavioral data that the model operates on to give its prediction.

4.1.2. Predicted score by model embedded in wearable device

This is followed by an analysis of the data, which results in the creation of a prospective score. The machine learning model applied to the system analyzes the data inputted by the sensors into the system, and in this record, one of the output of the digital_wellbeing_score is 35.0. This is a one-time quantitative measure of a user's current well-being status, and a decision-making process then leads to an additional stage.

4.1.3. Decision based on Predicted score

This calculated score is used to make a decision by the system as indicated in the pink box at the left. The framework is within a specific range of the user status with a score of 35.0, which is Critical Well-being Alert. This brings about an overflow of direct and rough suggestions. The system implies certain human behaviors, including a desperate turn to mental health, the limitation of online space to the minimum, and mindfulness. In the meantime, it provides recommendations on wearable electronics, including the addition of reminders to help with sleep hygiene, enabling relaxation mode, and sending emergency support messages in the event of connectivity issues.

4.1.4. Decision on counterfactuals for increasing score to 80.0

The last element of the figure is the decision on counterfactuals, which is in the pink box on the right. This is an essential aspect of proactive nature of the system. It not only indicates the immediate problem but also demonstrates to the user what particular behavior changes are required to attain a desired score of 80.0, which is the status

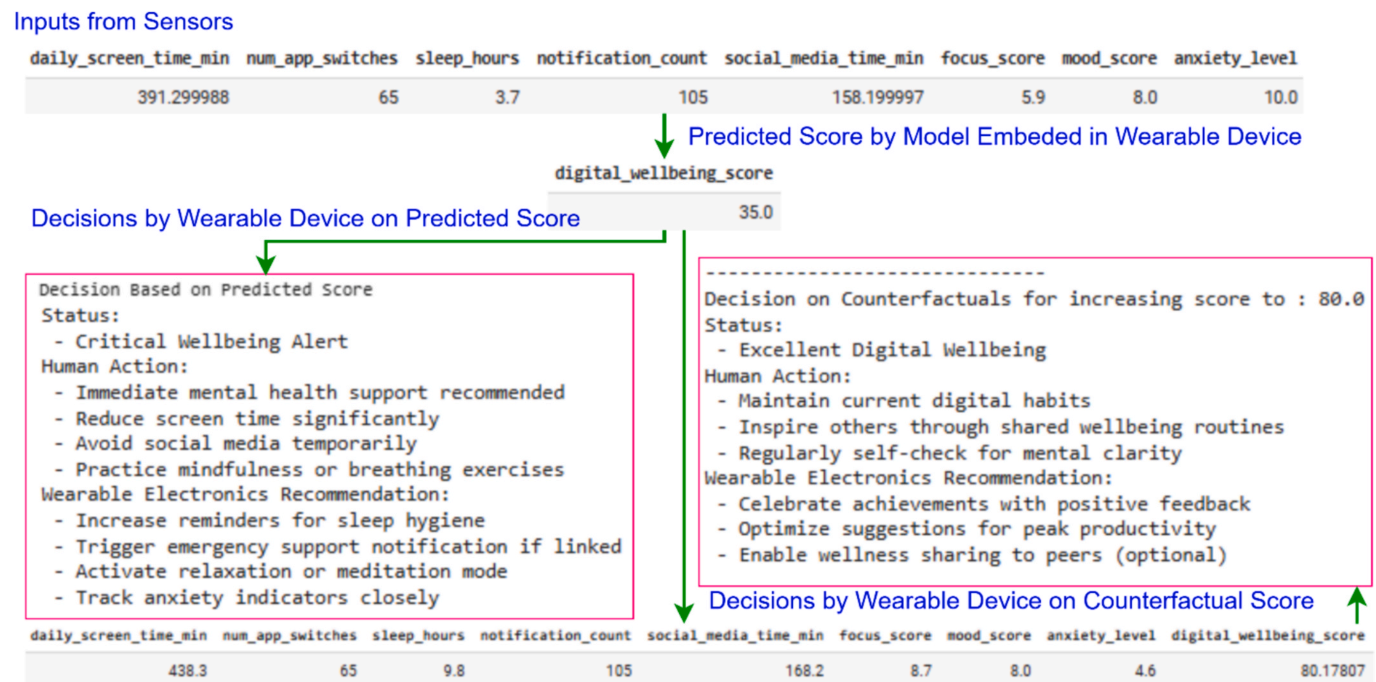

Fig. 11. Automatic Decisions by Proposed Work for Case Study Record 56.

of an "Excellent Digital Well-being. The recommended human behaviors include healthy digital practices and regular self-assessments to monitor their mental state. The wearable electronics recommendations are shifted to strengthen positive behaviors, including positive feedback by celebrating consistency and maximizing suggestions to achieve maximum productivity. By providing such a counterfactual situation, the framework offers a clear and data-driven roadmap for users to pursue in order to enhance their well-being.

4.2. *Automatic decisions by proposed work embedded in a wearable device for case study Record 213*

The illustration of how the system makes decisions regarding a user with another well-being status is clearly illustrated in Fig. 12, which is named Automatic Decisions by Proposed Work Case Study Record 213. It follows the same reasoning flow as the former figure, but with a different set of data, which leads to other suggestions.

Fig. 12 starts with the Inputs of Sensors, which are the data that were recorded at Record 213. The data that this user has is such that the user's daily_screen_time_min is 397.7, sleep_hours 6.8, and her anxiety_level of 5.1. This information is inputted into the built-in model and processed.

The model analyzes this input and a Predicted Score is produced with the help of the model installed in the Wearable Device. In this case study, the model predicts a digital wellbeing score of 63.0. This score, which is not within the same range as in the case above, determines the kind of intervention that the system will offer.

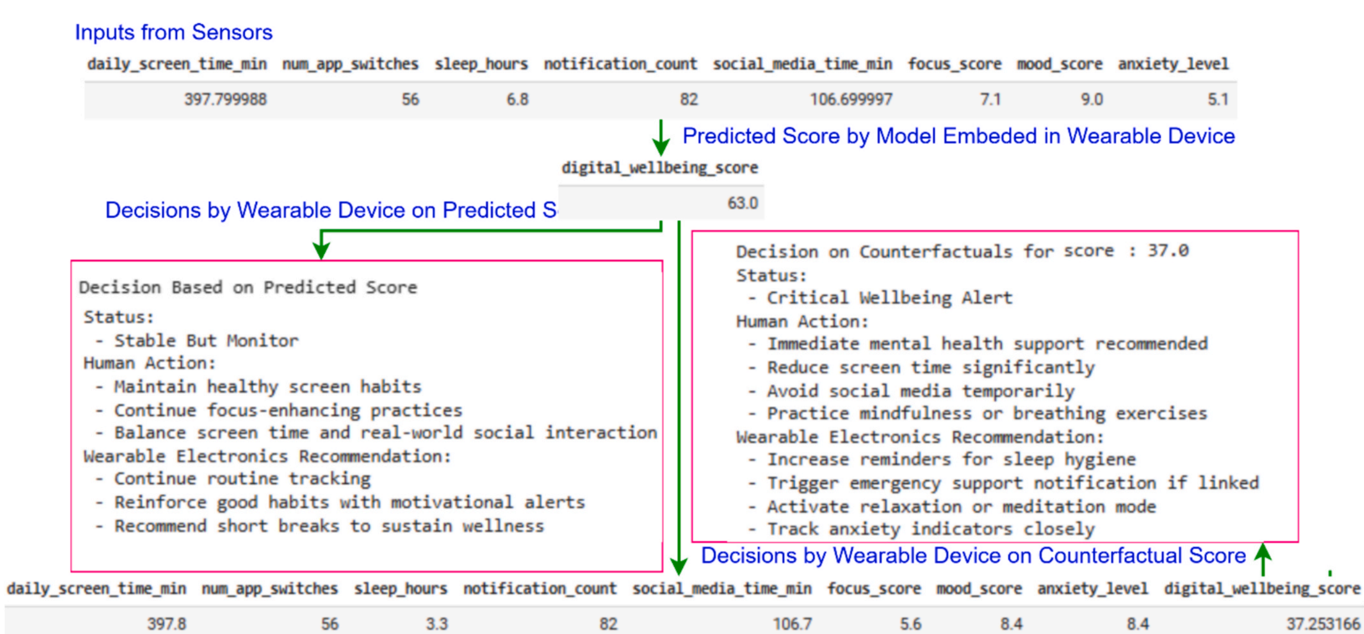

Fig. 12. Automatic Decisions by Proposed Work for Case Study Record 213.

According to the forecasted score of 63.0, the framework triggers a Decision Based on Predicted Score (the left pink box). The classification of the user's system status as 'Stable but Monitor' and a series of recommendations to continue good habits present the user with the opportunity to maintain their current level of good habits. The proposed "Human Actions" will involve keeping healthy screen time and persisting with the focus-enhancing practices. These actions are supported with the recommendations provided in the Wearable Electronics Recommendations, which imply the further routine monitoring, encouragement of positive habits, and advice on taking short breaks to maintain wellness.

Lastly, there is a figure that shows a Decision on Counterfactuals with a score of 37.0 (the correct pink box). This component of the system is meant to teach the user by providing them with an idea of what behavioral modifications would result in a decreased status in "Critical Well-being Alert. The counterfactual analysis reveals that a significant change in the amount of sleep to 3.3 h and a decline in the focus score to 5.6, among other factors, may lead to a drastic decline in the respondents' well-being scores. Introducing such information, the system emphasizes the necessity of having good habits and gives a clear image of the outcomes of the negative behavioral changes.

4.3. Comparison with Similar studies

Tables 8 and Table 9 together indicate the better functionality and effectiveness of the developed well-being prediction framework. Table 8 demonstrates that the Ridge Regression model with counterfactual explainability is more effective in comparison with several state-of-the-art techniques, such as the use of neural networks and ensemble models, as the Ridge Regression model with counterfactual explainability has a higher R 2 and much lower MSE and RMSE values. Table 9 also puts the contribution into further context by noting that the current methods do not offer interpretability or actionable outputs. Conversely, the described framework converts ongoing well-being measurements into visual explanations and behavior-specific suggestions, which users can understand, sealing essential voids in prediction and user-focused decision support of wearable-based mental health applications.

4.4. Discussion

The results presented in Tables 8 and 9 validate the effectiveness and originality of the proposed framework across both predictive performance and functional capabilities. From a performance standpoint, Table 8 shows that the Ridge Regression model, when combined with counterfactual explainability, significantly outperforms more complex models such as neural networks and ensemble methods. Specifically, it achieves the highest R^2 score (0.9996) and the lowest MSE (0.0275) and RMSE (0.166), indicating both precision and generalization strength. This performance is achieved with a non-complex and interpretable model, reinforcing the notion that explainability need not compromise predictive quality.

Table 8
Prediction of Well-Being Score from the Proposed Model Compared with Similar Works.

Model Used	Complex	XAI	R^2 Score	MSE	RMSE
Physics-Informed Neural Network [28]	Yes	Yes	0.9919		0.0362
Supervised Machine Learning [29]	Moderate	No			
CatBoost Regressor [30]	Yes	No	0.31	782.30	27.97
Multiple algorithms across 54 studies [31]	Yes	No			3.76
Random Forest [32]	Yes	No			~1.5
Ridge Regression + counterfactual XAI	No	Yes	0.9996	0.0275	0.166

Table 9
Comparison of Proposed Framework for Wearable Device Actions with Previous Works.

Task / Method	Demerits (lack of interpretability or actionable insight)	Proposed Work Advantage
LSTM autoencoder anomaly detection with SHAP (F1 ≈ 0.80) [9]	Alerts anomalies, but lacks user-level feature adjustments.	Predicts a well-being score and suggests behavioral changes with visual explanations.
LightGBM stress/ anxiety classification with sensors (ROC AUC ≈ 0.72) [10]	Classification-only; no regression or score-based decisions.	Translates data into a well-being score, actionable category, and recommendations.
Burnout biomarkers studies review [11]	Lacks interpretable and actionable predictive models.	Introduces an explainable regression model with tailored advice.
Systematic review of XAI in wearable health data [12]	Transparency gap; few decision support pipelines.	Uses Ridge regression with counterfactual logic for human actions and suggestions.
Symbolic regression for mood state (>99 % accuracy) [13]	No actionable guidance for user behavior.	Extended to continuous regression with status mapping and actionable suggestions.
Accelerometry-based foundation models for health outcomes [14]	Lacks well-being scoring and decision logic.	Enables low-power score prediction and counterfactual advice.
Deep autoencoder stress detection from BVP (accuracy ≈ 93–97 %) [15]	High-frequency detection, but no scoring or recommendations.	Converts detection into scoring with recommendations.
Study linking device use, sensor data, and mental health [16]	No predictive model or explainable framework.	Trains an interpretable regression model with actionable outputs.
AI/ML wearable architectures review [17]	Lacks predictive scoring and decision support.	Offers regression-based scoring, status classification, and real-time suggestions.
Smartwatch-based mental health monitoring review [18]	Aggregates findings but lacks decision logic or interventions.	Proposes a model that scores well-being, categorizes status, and offers counterfactual recommendations.

Table 9 extends this comparison by evaluating the qualitative utility of the model in real-world digital well-being applications. Unlike prior methods, which either lack transparency or fail to provide actionable insights, the proposed framework uniquely combines interpretable regression, LIME-based feature attribution, and counterfactual reasoning. This enables both users and systems to understand why a given well-being score was predicted and how behavioral changes can be made to improve it. Furthermore, the dual-layered recommendations—for both human action and device-level response—offer a distinctive advantage not found in earlier models.

Collectively, the comparisons underscore the framework's contribution in filling a twofold gap: (1) accurate and explainable well-being prediction, and (2) personalized, real-time feedback suitable for deployment in edge-enabled wearable systems. These capabilities distinguish the proposed system as a robust, interpretable, and actionable alternative to the prevailing state of the art.

5. Conclusion

5.1. Recapitulation

This study presents an interpretable and intelligent machine learning framework for predicting digital well-being scores using features collected from wearable devices. The proposed system is built upon a Ridge Regression model and enhanced with explainable AI techniques—namely, LIME visualizations and counterfactual reasoning. It achieves a near-perfect R^2 value of 0.9996, with low MSE (0.0275) and RMSE (0.166), demonstrating strong performance in estimating continuous well-being scores.

Rather than offering raw numerical predictions, the framework contextualizes scores into decision categories: Critical, Needs Improvement, Stable, and Excellent, each triggering tailored user actions. For example, scores above 75 prompt reinforcement of healthy digital behaviors, while scores below 40 result in recommendations such as reducing screen time, improving sleep, and engaging in mindfulness practices. These suggestions are conveyed in real time and can be executed through wearable devices, supporting continuous behavior tracking and self-regulation.

This model differs from prior studies that primarily focus on binary or multi-class classification tasks. Existing models, including those based on LightGBM, LSTM autoencoders, or symbolic regression, often lack interpretability, do not provide behavioral feedback, and are rarely designed for integration with wearable systems. In contrast, the proposed framework offers fine-grained scoring, transparency, and personalized decision support, effectively closing the gap between prediction and actionable insight.

The system has been implemented and validated using real-world data and demonstrated through visual output case studies. It is optimized for low-power edge deployment, making it suitable for mobile health applications and real-time monitoring in both urban and remote environments.

5.2. Future work

While the current framework successfully integrates prediction, interpretability, and intervention, several avenues remain open for future research:

- Multimodal Data Fusion: Incorporating additional sensor modalities, such as audio, GPS, and environmental data, could enhance the richness and reliability of well-being assessments.
- Personalized Learning: Future iterations can employ adaptive learning techniques to tailor models more specifically to individual users' baseline behavior and context.
- Clinical Validation: Collaborations with healthcare professionals and longitudinal trials will be essential to assess the clinical effectiveness and usability of the system in real-world settings.
- Privacy-Preserving Training: Implementing federated learning or secure multiparty computation can further enhance data privacy, especially during model updates on distributed wearable devices.
- Gamification and Engagement: Integrating motivational feedback, behavioral nudging, or gamified incentives could increase user engagement with well-being recommendations over time.

By addressing these directions, the proposed system can evolve into a robust, clinically validated, and user-centered solution for managing digital health and lifestyle habits in a scalable and ethical manner.

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Data Availability.

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

CRediT authorship contribution statement

Sheikh Muhammad Saqib: Conceptualization, Methodology, Writing – review & editing. **Tehseen Mazhar:** Methodology, Writing – original draft, Writing – review & editing. **Amal Al-Rasheed:** Validation, Visualization, Writing – original draft. **Muhammad Usman Tariq:** Formal analysis, Resources, Validation, Visualization. **Muhammad Amir Khan:** Conceptualization, Validation, Visualization. **Tariq Shahzad:** Data curation, Formal analysis, Resources, Validation. **Sunawar Khan:** Data curation, Formal analysis, Investigation. **Habib Hamam:** Conceptualization, Formal analysis, Investigation, Methodology, Writing – review & editing.

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