# A Review on Deep Learning for Quality of Life Assessment Through the Use of Wearable Data

Vasileios Skaramagkas, Ioannis Kyprakis, *Student Member, IEEE*, Georgia S. Karanasiou, Dimitris I. Fotiadis, *Fellow, IEEE*, and Manolis Tsiknakis, *Member, IEEE*

***Abstract*—Quality of Life (QoL) assessment has evolved over time, encompassing diverse aspects of human existence beyond just health. This paper presents a comprehensive review of the integration of Deep Learning (DL) techniques in QoL assessment, focusing on the analysis of wearable data. QoL, as defined by the World Health Organisation, encompasses physical, mental, and social well-being, making it a multifaceted concept. Traditional QoL assessment methods, often reliant on subjective reports or informal questioning, face challenges in quantification and standardization. To address these challenges, DL, a branch of machine learning inspired by the human brain, has emerged as a promising tool. DL models can analyze vast and complex datasets, including patient-reported outcomes, medical images, and physiological signals, enabling a deeper understanding of factors influencing an individual's QoL. Notably, wearable sensory devices have gained prominence, offering real-time data on vital signs and enabling remote healthcare monitoring. This review critically examines DL's role in QoL assessment through the use of wearable data, with particular emphasis on the subdomains of physical and psychological well-being. By synthesizing current research and identifying knowledge gaps, this review provides valuable insights for researchers, clinicians, and policymakers aiming to enhance QoL assessment with DL. Ultimately, the paper contributes to the adoption of advanced technologies to improve the well-being and QoL of individuals from diverse backgrounds.**

***Index Terms*—Deep learning, healthcare, machine learning, quality of life, wearable data.**

***Impact Statement*—This review highlights the transformative potential of deep learning techniques and wearable technology in assessing physical and psychological aspects of Quality of Life, enabling more personalized and accurate healthcare interventions.**

Received 1 October 2024; revised 26 November 2024 and 2 January 2025; accepted 2 January 2025. Date of publication 14 January 2025; date of current version 24 January 2025. This work was supported by the EU Horizon 2020 project CARDIOCARE under Grant Agreement 945175. The review of this article was arranged by Editor Paolo Bonato.
*(Corresponding author: Vasileios Skaramagkas.)*

Vasileios Skaramagkas and Manolis Tsiknakis are with the Biomedical Informatics and eHealth Laboratory, Department of Electrical and Computer Engineering, Hellenic Mediterranean University, 71410 Heraklion, Greece, and also with the Institute of Computer Science, Foundation for Research and Technology Hellas (FORTH), 70013 Heraklion, Greece (e-mail: vskaramag@ics.forth.gr).

Ioannis Kyprakis is with the Biomedical Informatics and eHealth Laboratory, Department of Electrical and Computer Engineering, Hellenic Mediterranean University, 71410 Heraklion, Greece, also with the Institute of Computer Science, Foundation for Research and Technology Hellas (FORTH), 70013 Heraklion, Greece, and also with the Department of Science et Techniques, University of Burgundy, 21000 Dijon, France.

Georgia S. Karanasiou and Dimitris I. Fotiadis are with the Unit of Medical Technology Intelligent Information Systems, University of Ioannina, 45110 Ioannina, Greece, and also with the Biomedical Research Institute, FORTH, 45110 Ioannina, Greece.

This article has supplementary downloadable material available at https://doi.org/10.1109/OJEMB.2025.3526457, provided by the authors.

Digital Object Identifier 10.1109/OJEMB.2025.3526457

## I. Introduction

The notion of Quality of Life (QoL) has been examined from multiple perspectives, resulting in the recognition that health-related QoL and total QoL are frequently synonymous. The World Health Organisation (WHO) characterises health as a holistic condition of physical, mental, and social well-being, underscoring its importance in improving quality of life. In addition to health, QoL includes employment capacity, social support, and the physical environment [1]. Researchers have suggested that QoL can be examined from several perspectives, such as psychological, economic, and medical, hence complicating its definition and assessment [2].

Conventional approaches to evaluating QoL have depended on informal enquiries by healthcare professionals, which may be subjective and variable. Two principal methodologies for systematic assessment have arisen: (1) validated patient-reported outcomes (PROs) instruments that gather subjective data [3]; and (2) objective data acquisition via technologies that record physiological signals and behaviours [3]. In response to the necessity for a thorough Quality of Life evaluation tool, the WHO created the WHOQOL assessment instrument, which includes many domains such as physical health, mental well-being, relationships, and environmental factors [4] (Fig. 1).

Recently, a paradigm change in QoL assessment has occurred with the incorporation of Deep Learning (DL) approaches, which utilise complicated datasets to improve comprehension of QoL domains [6]. This innovation facilitates the analysis of many data sources, such as PROs, medical imaging, and

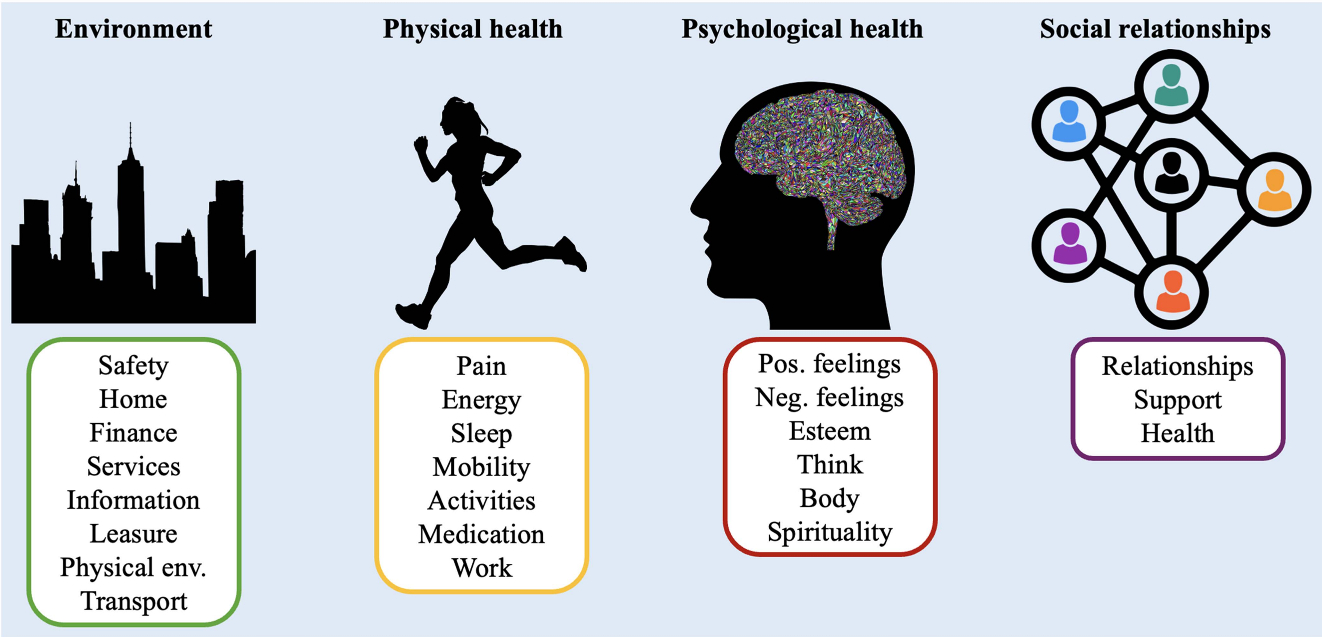


**Fig. 1.** WHOQOL instrument domains and subdomains [5].

physiological signals, yielding enhanced insights into the determinants of quality of life [7]. Wearable technologies have significantly altered the landscape by providing continuous, real-time data on vital signs and other health parameters, thus improving the precision of quality of life assessments [8], [9]. This review examines the function of deep learning approaches in evaluating the physical and psychological health subdomains of QoL, emphasising the progress and prospective applications of wearable technology in this emerging and critical healthcare sector [10].

## II. Physical Health Assessment

The maintenance of physical health is an essential aspect that contributes significantly to an individual's holistic well-being. It comprises a broad spectrum of factors pertaining to the physiological functioning and overall welfare of the human body [11]. One of these factors, Human Activity Recognition (HAR), has progressed markedly due to the emergence of DL, utilising wearable sensor data to precisely categorise activities of daily living (ADL) such as walking, jogging, and driving. Convolutional Neural Networks (CNN) have exhibited remarkable efficacy in extracting spatial characteristics from sensor data, as evidenced by Dua et al. [12], where a CNN-GRU hybrid attained an accuracy of 96.00% across several datasets. Long Short-Term Memory (LSTM) networks, intended for sequential data, have proven effective, with Kuncan et al. [13] attaining 98.42% accuracy utilising Motif Patterns. Hybrid models such as CNN-LSTM [14] enhance performance, achieving accuracy levels of up to 99.00% on particular datasets. Recently, attention mechanisms and transformers have improved the accuracy of HAR, as demonstrated in Sarkar et al. [15] and Dirgova Luptakova et al. [16], where transformer-based models attained over 99.00% accuracy by effectively capturing temporal dependencies in sensor data. Nevertheless, numerous research, including those employing benchmark datasets like UCI-HAR, are constrained by restricted sample numbers and insufficient variety, which raises issues over their generalisability across populations with varying demographics or activity patterns. These constraints may impede the model's efficacy in varied real-world environments. Furthermore, datasets frequently inadequately represent the inherent diversity of human behaviours, leading to models that are tailored to certain, often idealised circumstances instead of the unpredictable nature of real-world situations.

Moreover, medication adherence, an essential element of effective therapy, has significantly improved with DL algorithms and wearable data, providing real-time feedback and accuracy in monitoring. Odhiambo et al. [17] used a Deep Neural Network (DNN) with accelerometer data from smartwatches to identify involuntary movements associated with medicine, attaining a precision of 96.50%. CNNs have been effectively utilised, as demonstrated by Lee et al. [18], who employed a camera image sensor combined with wearable devices to monitor medicine adherence, achieving an accuracy of 92.70%. CNN-based approaches for monitoring chronic diseases and glucose levels have shown encouraging outcomes [19]. Pettas et al. [20] employed LSTM networks, recognised for their capability in temporal data processing, to identify audio events from inhalers, achieving accuracy rates as high as 94.00%, surpassing conventional approaches.

Energy and fatigue (EF) are essential measures of an individual's health and productivity, with precise measurement vital for evaluating overall well-being. Recent studies have investigated innovative techniques for identifying EF using wearable sensors and deep learning models. Sharma et al. [21] employed CNN to monitor wrist motions and recognise eating events with an accuracy of 89.00%, whereas Wang et al. [22] integrated CNNs with attention mechanisms to assess eating speed, achieving a minimal error of 0.11. Advancements in mental fatigue detection have been made by deep learning approaches; Wu et al. [23] employed a Contractive Sparse Auto-encoder to categorise fatigue states from EEG data, attaining an accuracy of 83.00%. Bai et al. [24] utilised a self-attention LSTM model for fatigue detection using ECG and actigraphy data, illustrating the efficacy of integrating temporal and attention mechanisms. Additional significant applications involve employing CNNs and BiLSTM for the detection of driver sleepiness [25], [26] and utilising HRV signals from wearables to assess driver fatigue [27], with these models attaining accuracy rates of up to 94.31%. Notwithstanding these developments, a trade-off exists between the accuracy of high-performing models, such as hybrid CNN-LSTM architectures, and the feasibility of their implementation on resource-limited wearable devices. The computational requirements of these models, especially when managing extensive datasets or real-time data streams, may hinder their deployment on devices with limited processing capacity or battery longevity. This requires the investigation of more computationally efficient algorithms that can sustain high accuracy while remaining practical for wearable devices.

Mobility is another essential aspect of public health, encompassing physical mobility, ambulation, and transportation, all of which enhance an individual's QoL [28]. GPS-enabled wearables enable the assessment of life-space mobility, which is associated with social support and gait speed [29], whilst accelerometers monitor velocity and physical activity [30]. Numerous research efforts utilise wearable sensors to evaluate fall risk and mobility challenges, especially among the older population. Kulurkar et al. [31] attained a 95.87% accuracy in fall detection utilising LSTM and IoT-based systems. In patients with Parkinson's Disease, freezing of gait (FOG) was accurately predicted utilising transformer-based topologies combined with BiLSTM, resulting in elevated specificity and sensitivity [32].

Pain perception is a multifaceted and subjective experience that presents difficulties for objective assessment [33]. Recent breakthroughs in wearable technologies, including electrodermal activity (EDA) sensors and DL algorithms, provide novel methods for pain quantification, hence improving quality of life evaluations. Gkikas et al. [34] used multi-task learning (MTL) neural networks with ECG data, enhancing the precision of pain assessment. Rojas et al. [35] employed functional near-infrared spectroscopy and a BiLSTM model to attain 90.60% accuracy in evaluating pain in non-communicative patients. Pouromran et al. [36] enhanced pain intensity classification using a customised BiLSTM model, achieving a f1-score of 0.81 and an AUROC of 0.93 across multiple pain states. Hu et al. [37] proved the efficacy of LSTM in chronic pain identification, attaining precision and recall rates of 97.20% via balance and body sway analysis. Wang et al. [38] investigated protective behaviour recognition with layered LSTM methodologies, achieving an ideal F1-score of 0.82. Furthermore, Yu et al. [39] employed EEG signals to objectively assess pain, attaining classification accuracy of 97.37%, via CNN-based models.

Additionally, sleep is a vital physiological condition marked by a transient loss of consciousness and modified cerebral activity, serving a fundamental function in both physical and mental well-being [40]. Emerging wearable technology and sophisticated deep learning approaches are crucial for precisely measuring sleep, improving personal understanding of sleep patterns, and aiding healthcare professionals in detecting sleep problems and refining treatment strategies. The NetHealth dataset [41], which examined data from 698 college students, revealed that CNN could proficiently evaluate sleep quality, attaining a mean absolute error (MAE) of roughly 0.04. Furthermore, Yildirim et al. [42] presented a 1D-CNN model that automated the classification of sleep stages utilising polysomnogram (PSG) data, attaining accuracies ranging from 91.00% to 98.06%. Mousavi et al. [43] created SleepEEGNet, which employed single-channel EEG data to attain an accuracy of 84.26% by integrating CNN and sequence-to-sequence models. In contrast, Supratak et al. [44] merged CNN and BiLSTM networks in the DeepSleepNet model, achieving an accuracy of 86.20%. Furthermore, actigraphy sensors have shown efficacy in forecasting sleep efficiency, with CNN achieving the best accuracy of 97.30% [45]. LSTM models, as emphasised by Phan et al. [46], successfully forecasted sleep quality via physical activity data, attaining an accuracy of 61.00. Finally, Matsumori et al. [47] utilised a hybrid CNN-LSTM model with a lightweight EEG sensor, attaining an accuracy of 78.60%, equivalent to clinical PSG systems.

Lastly, work capacity, as defined by the American College of Sports Medicine (ACSM), refers to the maximum physical work an individual can perform, assessed through power output or endurance and influenced by factors like cardiorespiratory fitness and muscular strength [48]. Traditional evaluations have relied heavily on self-report instruments, which often suffer from reliability issues due to biases and recall problems [49]. The Work-ability Support Scale (WSS) effectively measures vocational capability after disability, covering physical, cognitive, and social domains [50]. Other assessments, such as the Functional Capacity Evaluation (FCE) and the Work Ability Index (WAI), focus on job-specific physical and cognitive requirements [51]. The Work Capacity Test (WCT), used by organizations like the U.S. Forest Service, assesses physical capabilities for demanding roles [52]. Wearable activity trackers can quantify many work capacity factors, making them useful for physically demanding jobs. However, like mobility, we assume that the subset of work capacity that can be evaluated using DL using wearable sensor data is closely connected with ADL evaluation.

For a comprehensive summary of studies employing wearable devices for physical health assessment, including datasets, sensors, and methodologies, we refer readers to Table I in the supplementary material.

## III. Psychological Health

The QoL of an individual is significantly influenced by their physiological health, encompassing various dimensions such as feelings, self-esteem, memory, spirituality, and body image [53]. The importance of physiological health within the larger framework of QoL becomes apparent when we consider its direct influence on many domains. One such domain, feelings, encompassing both positive and negative states, are fundamental to well-being and QoL [54]. Recent advancements in wearable technology have significantly improved the ability to identify emotions by monitoring physiological signals such as heart rate variability, skin conductance, and facial expressions [55]. Research employing DL methodologies has demonstrated this potential; for instance, the eSEE-d database utilises eye-tracking data for emotion estimation, achieving an accuracy of up to 92.00% for positive valence [56]. Furthermore, systems integrating sensors with deep learning models, such as a smartwatch-based adaptive system for multi-sensory emotion detection, have attained an accuracy of 74.30% in identifying arousal and valence [57]. In addition, self-supervised learning has shown robustness to data degradation, achieving 81.00% accuracy in emotion recognition [58], while emotion recognition in older adults using LSTM networks has reached accuracies of up to 95.00% [59]. Moreover, hybrid CNN-LSTM models have demonstrated efficacy with precision rates as high as 99.00% [60]. Large Language Models (LLMs) like GPT have been utilized for analyzing patient narratives and emotion estimation, complementing sensor-based methods for psychological health assessment. For example, recent studies [61] have demonstrated how these models can process unstructured text data to derive insights into emotional well-being, thereby enriching the understanding of QoL dimensions.

Self-esteem, which refers to an individual's self-acceptance and self-regard, is shaped by personal and cultural standards and their perceived competency in essential life domains [62]. Traditionally, self-esteem evaluations have relied on self-report instruments such as the Rosenberg Self-Esteem Scale (RSE) and the Single Item Self-Esteem Scale (SISE) [63], [64]. Instruments like the Multidimensional Self-Esteem Inventory (MSEI) and the Contingency of Self-Worth Scale (CSWs) focus on specific dimensions of self-esteem [65], [66]. However, wearable technology presents innovative yet complex possibilities for measuring self-esteem. A novel method utilising EEG data and CNN models has achieved an accuracy exceeding 79.00% in differentiating between high and low self-esteem [67]. Although CNN-LSTM models demonstrate great accuracy in emotion recognition, their lack of explainability hinders healthcare practitioners from trusting and implementing these methods in practice. The opaque nature of deep learning models hinders the interpretability of outcomes, particularly in sensitive domains like psychological health, where practitioners require clear and comprehensible insights for informed decision-making. Explainable AI (XAI) models are necessary to overcome these concerns and enhance trust in such technologies for clinical application.

Spirituality, which encompasses the acknowledgment of a higher force and the pursuit of meaning beyond sensory experience, poses unique challenges for technological quantification [68]. Instruments such as the Spiritual Well-Being Scale (SWBS) [69], the Spiritual Needs Questionnaire (SpNQ) [70], and the Spirituality Questionnaire [71] are commonly employed to evaluate spiritual well-being. Despite the promise offered by wearable sensors and deep learning for quality of life assessments, the subjective and contextual nature of spirituality presents considerable obstacles, as physical data may inadequately represent spiritual experiences.

Thinking, comprising fundamental mental processes such as perception, memory, problem-solving, and decision-making, is vital for numerous aspects of life, including emotional control and communication. Recent advancements in DL have facilitated the classification of cognitive states through wearable devices. For example, integrating EEG data with CNN models has achieved an accuracy of up to 96.70% in classifying cognitive workload in drivers [72]. Similarly, DL approaches employing EEG and eye-tracking data have shown great accuracy (up to 97.00%) in identifying cognitive effort and mental burden [73]. These methodologies, despite facing obstacles, exhibit great potential for enhancing cognitive evaluation and, consequently, QoL.

Body image refers to an individual's cognitive and emotional perceptions regarding their physique, encompassing elements such as form, size, and attractiveness [74]. While wearable devices like smartwatches and activity trackers can gather data on physical metrics such as blood pressure and bodily movements [75], they are limited in their ability to encapsulate the intricate, subjective aspects of body image, including body acceptance and self-perception [76]. A comprehensive evaluation of body image necessitates an amalgamation of objective metrics and self-reported instruments, including the Body-Image Acceptance and Action Questionnaire [77] and the Body Image Scale [78]. By integrating these diverse elements, we can gain a more nuanced understanding of psychological health and its impact on overall quality of life.

For a comprehensive summary of studies employing wearable devices for psychological health assessment, we refer readers to Table II in the supplementary material.

## IV. Publicly Available Datasets

This section discusses the strengths and weaknesses of datasets related to QoL subdomains that include wearable sensor data and are publicly accessible. Table I highlights significant variation in participant data, with sample sizes ranging from 4 ("OPPORTUNITY") to 700 ("NetHealth") and ages spanning 18 to 78 years, as seen in the "Sleep-EDF" dataset. Such diversity enhances the generalizability of findings across age cohorts. Gender distribution also varies; for instance, "BioVid Heat Pain" includes 43 females and 44 males, while "MHEALTH" lacks gender-specific data. Demographic diversity aids in understanding how factors like age and gender influence QoL assessments through wearable data [105].

The datasets encompass a wide array of stimuli and activities, demonstrating the adaptability of wearable technology in evaluating various facets of daily life. For instance, "Extra-sensory" assesses 51 behavioral activities, whereas "MIT/BIH PSG" concentrates on overnight sleep recordings. Numerous datasets, like "UCI-HAR," "WISDM," and "PAMAP," focus on ADL, rendering them especially pertinent for quality of life evaluations in this subdomain. In contrast, datasets such as "MIT/BIH PSG"

TABLE I
SUMMARY OF IDENTIFIED PUBLICLY AVAILABLE DATASETS CONTAINING WEARABLE DATA AND STIMULI RELATED TO QOL DOMAINS

| Dataset | Subjects | Age | Gender (F/M) | Stimuli | Wearable data | Subdomain |
|---|---|---|---|---|---|---|
| UCI-HAR [79] | 30 | 19-48 | | 6 ADL activities | ACC, GYRO (50 Hz) | ADL |
| WISDM [80] | 36 | | | 6 ADL activities | ACC (20 Hz) | ADL |
| PAMAP [81] | 9 | 27.2±3.3 | 1/8 | 18 ADL activites | ACC, GYRO, HR (100 Hz) | ADL |
| Extra-sensory [82] | 60 | 18-42 | 34/26 | 51 behavioural activities | ACC, GYRO, MAG (40Hz), Watch ACC (25Hz), GPS, Audio | ADL |
| OPPORTUNITY [83] | 4 | | | 5 ADL morning activities | ACC, GYRO, MAG (30 Hz) | ADL |
| UniMib-SHAR [84] | 30 | 18-60 | 6/24 | 9 ADL activities, 8 falls | ACC (50 Hz) | ADL |
| Daily and Sport Activities [85] | 8 | 20-30 | 4/4 | 19 ADL and sports activities | ACC, GYRO, MAG (25 Hz) | ADL |
| REALWORLD16 [86] | 15 | 31.9±12.4 | 8/7 | 6 ADL activities | ACC, GYRO, MAG, Location, Audio | ADL |
| MHEALTH [87] | 16 | | | 12 physical activities | ACC, GYRO, HR, ECG (50 Hz) | ADL |
| BioVid Heat Pain [88] | 87 | 20-65 | 43/44 | Heat stimulus | ECG, EMG, SCL | Pain |
| EmoPain [89] | 50 | 44 (mean) | 29/21 | Physiotherapy activities | ACC, GYRO, EMG (1 kHz) | Pain |
| MobiAct [90] | 57 | 20-47 | 15/42 | Falls | ACC, GYRO (20 Hz) | Mobility |
| MIT/BIH PSG [91] | 16 | 32-56 | 0/16 | Whole-night sleep recordings | EEG, EOG, EMG, BVP, OS, RS, CV (250 Hz) | EF |
| FD I&II [92] | 61 | | | Whole-day eating episodes | IMU (64 Hz) | EF |
| Sleep-EDF [93] | 22 | 18-78 | 7/15 | Whole-night sleep recordings | EEG, EOG, EMG (50 Hz) | EF/Sleep |
| NetHealth [94] | 700 | | | ADL activities, sleeping task | HR, Sleep biomarkers | Sleep |
| Sleep-EDFX [95] | 24 | 18-79 | 15/9 | Whole-night sleep recordings | EEG, EOG, EMG (50 Hz) | Sleep |
| MASS [96] | 200 | 18-76 | 103/97 | Whole-night sleep recordings | EEG, EOG, EMG, ECG, RS (256 Hz) | Sleep |
| Apnea ECG [97] | 27 | 27-63 | 6/21 | Whole-night sleep recordings | ECG (100 Hz) | Sleep |
| eSEE-d [56] | 48 | 18-47 | 27/21 | Emotion evoking videos | Eye tracking metrics | Feelings |
| AffectiveROAD [98] | 10 | 24-34 | 5/5 | Real world driving sessions | BVP, ACC (36 Hz), EDA (4 Hz), HR (1 Hz), ECG, BR, ST (4 Hz) | Feelings |
| CASE [99] | 30 | 22-37 | 15/15 | Emotion evoking videos | ECG, BVP, EMG, EDA (1000 Hz) | Feelings |
| CLAS [100] | 60 | 20-50 | | Emotion evoking videos, mentally demanding tasks | ECG, PPG, EDA, ACC (256 Hz) | Feelings |
| K-EmoCon [101] | 32 | 19-36 | 12/20 | Naturalistic conversations | ECG (1 Hz), EEG (125 Hz), BVP (64 Hz), EDA (4 Hz), BT (4 Hz), ACC (32 Hz), HR (1 Hz) | Feelings |
| PPG-DaLiA [102] | 24 | 26.9±4.8 | 14/10 | Walking activities | PPG, ECG, ACC, GYRO | Feelings |
| WESAD [103] | 15 | 24-35 | 3/12 | Sedentary activities | BVP (64 Hz), ACC (32 Hz), EDA (700 Hz), BT (700 Hz),EMG (700 Hz), BR, ECG (700 Hz) | Feelings |
| DEAP [104] | 32 | 19-37 | 16/16 | Music videos | EEG (512 Hz) | Feelings |

ACC: Accelerometer, GYRO: Gyroscope, HR: Heart Rate, MAG: Magnetometer, GPS: Global Positioning System, EEG: Electroencephalogram, EOG: Electrooculogram, EMG: Electromyogram, BVP: Blood Volume Pulse, OS: Oxygen Saturation, RS: Respiration, CV: Cardiovascular, ECG: Electrocardiogram, SCL: Skin Conductance Level, EDA: Electrodermal Activity, PSG: Polysomnography, BR: Breathing Rate, ST: Skin Temperature, BT: Body Temperature, PPG: Photoplethysmogram, UV: Ultraviolet radiation.

and “Sleep-EDF” focus on sleep-related stimuli, corresponding to the Energy and Fatigue, and Sleep (EF/Sleep) subdomains. This variability enables researchers to customize their inquiries to particular aspects of QoL. Furthermore, the datasets employ several wearable sensors, such as accelerometers (ACC), gyroscopes (GYRO), and electrocardiograms (ECG), to assess quality of life (QoL) thoroughly. The MHealth dataset integrates ACC, GYRO, heart rate (HR), and ECG data, rendering it suitable for assessing activities of daily living (ADL) in QoL research. Likewise, EEG and EMG data in “Sleep-EDFX” and “MASS” are customized for sleep-related subdomains. The emotional aspects of quality of life are examined in datasets such as “eSEE-d” and “CASE,” which utilize emotion-inducing films and record physiological signals like ECG and electrodermal activity (EDA). The diversity and richness of wearable data in these datasets provide a detailed examination of quality of life across many research requirements.

## V. Conclusion

In conclusion, integrating DL with wearable technology offers a promising approach to evaluating QoL, excelling in domains like physical and psychological well-being. Models like CNN and LSTM provide accurate insights into daily activities, medication adherence, and mental states through real-time, objective data often missed by self-reports. DL’s ability to process multimodal sensor data enables comprehensive, dynamic, and personalized QoL assessments. However, challenges remain regarding generalizability, data variability, and privacy. Limited datasets and demographic-specific studies hinder broader applicability, while subjective aspects like body image and spirituality pose integration difficulties. Real-world deployment faces hurdles like noisy data, battery constraints, and privacy concerns.

Looking ahead, innovations like explainable AI, federated learning, and edge computing promise more transparent, private, and real-time wearable data processing. Interdisciplinary collaboration is essential for advancing DL-driven QoL evaluations, paving the way for transformative impacts on healthcare and well-being.

## Conflict of Interest

The authors declare no conflict of interest.

## References


[1] J. R. Turner et al., “Quality of life,” in *Encyclopedia of Behavioral Medicine*. New York, NY, USA: Springer, 2013, pp. 1602–1603.

[2] A. Alexandrova, *A Philosophy for the Science of Well-Being*, vol. 1. Oxford, U.K.: Oxford Univ. Press, Aug. 2017.

[3] N. E. Mayo, S. Figueiredo, S. Ahmed, and S. J. Bartlett, “Montreal accord on patient-reported outcomes (PROs) use series–Paper 2: Terminology proposed to measure what matters in health,” *J. Clin. Epidemiol.*, vol. 89, pp. 119–124, Sep. 2017.

[4] World Health Organization, “WHOQOL User Manual,” *World Health Organization, Programme on Mental Health, Division of Mental Health and Prevention of Substance Abuse, WHO/MNH/MHP/98.4.Rev.1*. Geneva, Switzerland, 1998.

[5] World Health Organization. “WHOQOL-BREF: Introduction, administration, scoring, and generic version of the assessment,” *World Health Organization, An Abbreviated Quality of Life Assessment Instrument Developed by the World Health Organization*. Geneva, Switzerland, 1996.

[6] Z. Han, J. Zhao, H. Leung, K. F. Ma, and W. Wang, “A review of deep learning models for time series prediction,” *IEEE Sensors J.*, vol. 21, pp. 7833–7848, Mar. 2021.

[7] D. Garg, G. K. Verma, and A. K. Singh, “A review of deep learning based methods for affect analysis using physiological signals,” *Multimedia Tools Appl.*, vol. 82, pp. 26089–26134, Jul. 2023.

[8] V. Skaramagkas, A. Pentari, Z. Kefalopoulou, and M. Tsiknakis, “Multi-modal deep learning diagnosis of Parkinson’s disease—A systematic review,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 31, pp. 2399–2423, 2023.

[9] M. Xu, L. Guo, and H.-C. Wu, “Novel robust automatic brain-tumor detection and segmentation using magnetic resonance imaging,” *IEEE Sensors J.*, vol. 24, no. 7, pp. 10957–10964, Apr. 2024.

[10] S. M. A. Iqbal, I. Mahgoub, E. Du, M. A. Leavitt, and W. Asghar, “Advances in healthcare wearable devices,” *npj Flexible Electron.*, vol. 5, pp. 1–14, Apr. 2021.

[11] H. N. Rasmussen, M. F. Scheier, and J. B. Greenhouse, “Optimism and physical health: A meta-analytic review,” *Ann. Behav. Med.*, vol. 37, pp. 239–256, Jun. 2009.

[12] N. Dua, S. N. Singh, and V. B. Semwal, “Multi-input CNN-GRU based human activity recognition using wearable sensors,” *Computing*, vol. 103, pp. 1461–1478, Jul. 2021.

[13] F. Kuncan, Y. Kaya, Z. Yiner, and M. Kaya, “A new approach for physical human activity recognition from sensor signals based on Motif patterns and long-short term memory,” *Biomed. Signal Process. Control*, vol. 78, Sep. 2022, Art. no. 103963.

[14] R. Mutegeki and D. S. Han, “A CNN-LSTM approach to human activity recognition,” in *Proc. 2020 Int. Conf. Artif. Intell. Inf. Commun.*, Feb. 2020, pp. 362–366.

[15] A. Sarkar, S. K. S. Hossain, and R. Sarkar, “Human activity recognition from sensor data using spatial attention-aided CNN with genetic algorithm,” *Neural Comput. Appl.*, vol. 35, pp. 5165–5191, Mar. 2023.

[16] I. Dirgová Luptáková, M. Kubovčík, and J. Pospíchal, “Wearable sensor-based human activity recognition with transformer model,” *Sensors*, vol. 22, Jan. 2022, Art. no. 1911.

[17] C. O. Odhiambo, L. Ablonczy, P. J. Wright, C. F. Corbett, S. Reichardt, and H. Valafar, “Detecting medication-taking gestures using machine learning and accelerometer data collected via smartwatch technology: Instrument validation study,” *JMIR Hum. Factors*, vol. 10, May 2023, Art. no. e42714.

[18] H. Lee and S. Youm, “Development of a wearable camera and AI algorithm for medication behavior recognition,” *Sensors*, vol. 21, May 2021, Art. no. 3594.

[19] D. N. Thyde, A. Mohebbi, H. Bengtsson, M. L. Jensen, and M. Mørup, “Machine learning-based adherence detection of type 2 diabetes patients on once-daily basal insulin injections,” *J. Diabetes Sci. Technol.*, vol. 15, pp. 98–108, Jan. 2021.

[20] D. Pettas, S. Nousias, E. I. Zacharaki, and K. Moustakas, “Recognition of breathing activity and medication adherence using LSTM neural networks,” in *Proc. IEEE 19th Int. Conf. Bioinf. Bioeng.*, Oct. 2019, pp. 941–946.

[21] S. Sharma and A. Hoover, “Top-down detection of eating episodes by analyzing large windows of wrist motion using a convolutional neural network,” *Bioengineering*, vol. 9, Feb. 2022, Art. no. 70.

[22] C. Wang, T. S. Kumar, W. De Raedt, G. Camps, H. Hallez, and B. Vanrumste, “Eating speed measurement using wrist-worn IMU sensors in free-living environments,” *IEEE J. Biomed. Health Inform.*, vol. 28, pp. 5816–5828, Oct. 2024.

[23] E. Q. Wu et al., “Detecting fatigue status of pilots based on deep learning network using EEG signals,” *IEEE Trans. Cogn. Devel. Syst.*, vol. 13, no. 3, pp. 575–585, Sep. 2021.

[24] Y. Bai, Y. Guan, and W.-F. Ng, “Fatigue assessment using ECG and actigraphy sensors,” in *Proc. 2020 Int. Symp. Wearable Comput.*, Sep. 2020, pp. 12–16.

[25] U. Budak, V. Bajaj, Y. Akbulut, O. Atila, and A. Sengur, “An effective hybrid model for EEG-based drowsiness detection,” *IEEE Sensors J.*, vol. 19, no. 17, pp. 7624–7631, Sep. 2019.

[26] D. Utomo, T.-H. Yang, D. T. Thanh, and P.-A. Hsiung, “Driver fatigue prediction using different sensor data with deep learning,” in *Proc. 2019 IEEE Int. Conf. Ind. Cyber Phys. Syst.*, May 2019, pp. 242–247.

[27] H. Lee, J. Lee, and M. Shin, “Using wearable ECG/PPG sensors for driver drowsiness detection based on distinguishable pattern of recurrence plots,” *Electronics*, vol. 8, Feb. 2019, Art. no. 192.

[28] World Health Organization, *International Classification of Functioning, Disability and Health (ICF)*, 2nd ed. Geneva: World Health Organization, 2001.

[29] A. Kuspinar et al., "Modifiable factors related to life-space mobility in community-dwelling older adults: Results from the Canadian longitudinal study on aging," *BMC Geriatrics*, vol. 20, Jan. 2020, Art. no. 35.

[30] D. Thakur, A. Guzzo, and G. Fortino, "Attention-based multihead deep learning framework for online activity monitoring with smartwatch sensors," *IEEE Internet Things J.*, vol. 10, no. 20, pp. 17746–17754, Oct. 2023.

[31] P. Kulurkar, C. K. Dixit, V. C. Bharathi, A. Monikavishnuvarthini, A. Dhakne, and P. Preethi, "AI based elderly fall prediction system using wearable sensors: A smart home-care technology with IoT," *Meas.: Sensors*, vol. 25, Feb. 2023, Art. no. 100614.

[32] W. T. Mo and J. H. Chan, "Freezing of gait prediction using deep learning," in *Proc. 13th Int. Conf. Adv. Inf. Technol.*. New York, NY, USA: ACM, Dec. 2023, pp. 1–6.

[33] S. Gkikas and M. Tsiknakis, "Automatic assessment of pain based on deep learning methods: A systematic review," *Comput. Methods Programs Biomed.*, vol. 231, Apr. 2023, Art. no. 107365.

[34] S. Gkikas, C. Chatzaki, and M. Tsiknakis, "Multi-task neural networks for pain intensity estimation using electrocardiogram and demographic factors," *Commun. Comput. Inf. Sci.*, vol. 1856, pp. 324–337, 2023.

[35] R. F. Rojas, J. Romero, J. Lopez-Aparicio, and K. L. Ou, "Pain assessment based on fNIRS using Bi-LSTM RNNs," in *Proc. Int. IEEE/EMBS Conf. Neural Eng.*, May 2021, pp. 399–402.

[36] F. Pouromran, Y. Lin, and S. Kamarthi, "Personalized deep Bi-LSTM RNN based model for pain intensity classification using EDA signal," *Sensors*, vol. 22, Oct. 2022, Art. no. 8087.

[37] B. Hu, C. Kim, X. Ning, and X. Xu, "Using a deep learning network to recognise low back pain in static standing," *Ergonomics*, vol. 61, pp. 1374–1381, Oct. 2018, doi: 10.1080/00140139.2018.1481230.

[38] C. Wang, T. A. Olugbade, A. Mathur, A. C. Williams, N. D. Lane, and N. Bianchi-Berthouze, "Chronic pain protective behavior detection with deep learning," *ACM Trans. Comput. Healthcare*, vol. 2, pp. 1–24, Jul. 2021.

[39] M. Yu et al., "Diverse frequency band-based convolutional neural networks for tonic cold pain assessment using EEG," *Neurocomputing*, vol. 378, pp. 270–282, Feb. 2020.

[40] D. Kocevska et al., "Sleep characteristics across the lifespan in 1.1 million people from The Netherlands, United Kingdom and United States: A systematic review and meta-analysis," *Nature Hum. Behav.*, vol. 5, pp. 113–122, Jan. 2021.

[41] O. Kilic, B. Saylam, and O. D. Incel, "Sleep quality prediction from wearables using convolution neural networks and ensemble learning," in *Proc. 8th Int. Conf. Mach. Learn. Technol.*, Mar. 2023, pp. 116–120.

[42] O. Yildirim, U. B. Baloglu, and U. R. Acharya, "A deep learning model for automated sleep stages classification using PSG signals," *Int. J. Environ. Res. Public Health*, vol. 16, Feb. 2019, Art. no. 599.

[43] S. Mousavi, F. Afghah, and U. R. Acharya, "SleepEEGNet: Automated sleep stage scoring with sequence to sequence deep learning approach," *PLoS One*, vol. 14, May 2019, Art. no. e0216456.

[44] A. Supratak, H. Dong, C. Wu, and Y. Guo, "DeepSleepNet: A model for automatic sleep stage scoring based on raw single-channel EEG," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 11, pp. 1998–2008, Nov. 2017.

[45] A. Sathyanarayana et al., "Sleep quality prediction from wearable data using deep learning," *JMIR mHealth uHealth*, vol. 4, Oct. 2016, Art. no. e125.

[46] D. V. Phan, C. L. Chan, and D. K. Nguyen, "Applying deep learning for prediction sleep quality from wearable data," in *Proc. ACM Int. Conf. Med. Health Informat.*, Aug. 2020, pp. 51–55.

[47] S. Matsumori, K. Teramoto, H. Iyori, T. Soda, S. Yoshimoto, and H. Mizutani, "HARU sleep: A deep learning-based sleep scoring system with wearable sheet-type frontal EEG sensors," *IEEE Access*, vol. 10, pp. 13624–13632, 2022.

[48] D. Riebe, J. Ehrman, G. Liguori, and M. Magal, *ACSM's Guidelines for Exercise Testing and Prescription*. Philadelphia, PA, USA: Wolters Kluwer Health, Mar. 2018.

[49] R. S. Falck, S. McDonald, M. Beets, K. Brazendale, and T. Liu-Ambrose, "Physical activity measurement in older adult interventions: A systematic review and meta-analysis: 897 Board #293 May 27, 3:30 pm–5:00 pm," *Med. Sci. Sports Exercise*, vol. 47, pp. 247–248, May 2015.

[50] L. Turner-Stokes, J. Fadyl, H. Rose, H. Williams, P. Schlüter, and K. McPherson, "The work-ability support scale: Evaluation of scoring accuracy and rater reliability," *J. Occup. Rehabil.*, vol. 24, no. 3, pp. 511–524, 2014.

[51] J. Ilmarinen, "The work ability index (WAI)," *Occup. Med.*, vol. 57, pp. 160–160, Oct. 2006.

[52] United States Department of Agriculture Forest Service, "Wildland firefighter work capacity test (wct)," (n.d). *Safety and Work Capacity Guidelines for Wildland Firefighters*.

[53] P. Salovey, A. J. Rothman, J. B. Detweiler, and W. T. Steward, "Emotional states and physical health," *Amer. Psychol.*, vol. 55, pp. 110–121, Jan. 2000.

[54] J.-C. Chebat and R. Michon, "Impact of ambient odors on mall shoppers' emotions, cognition, and spending: A test of competitive causal theories," *J. Bus. Res.*, vol. 56, pp. 529–539, Jul. 2003.

[55] V. Skaramagkas et al., "Review of eye tracking metrics involved in emotional and cognitive processes," *IEEE Rev. Biomed. Eng.*, vol. 16, pp. 260–277, 2023.

[56] V. Skaramagkas et al., "eSEE-d: Emotional state estimation based on eye-tracking dataset," *Brain Sci.*, vol. 13, Mar. 2023, Art. no. 589.

[57] Z. Wang, Z. Yu, B. Zhao, B. Guo, C. Chen, and Z. Yu, "EmotionSense," *ACM Trans. Comput. Healthcare*, vol. 1, Sep. 2020, Art. no. 20.

[58] V. Dissanayake, S. Seneviratne, R. Rana, E. Wen, T. Kaluarachchi, and S. Nanayakkara, "SigRep: Toward robust wearable emotion recognition with contrastive representation learning," *IEEE Access*, vol. 10, pp. 18105–18120, 2022.

[59] F. Zeng, Y. Lin, P. Siriaraya, D. Choi, and N. Kuwahara, "Emotion detection using EEG and ECG signals from wearable textile devices for elderly people," *J. Textile Eng.*, vol. 66, pp. 109–117, Dec. 2020.

[60] Z. Lian, Y. Guo, X. Cao, and W. Li, "An ear wearable device system for facial emotion recognition disorders," *Front. Bioeng. Biotechnol.*, vol. 9, Jun. 2021, Art. no. 703048.

[61] R. Bommasani, "On the opportunities and risks of foundation models," Jul. 2022, *arXiv:2108.07258*.

[62] K. Wac and S. Wulfovich, Eds., *Quantifying Quality of Life: Incorporating Daily Life Into Medicine* (Health Informatics). Cham, Switzerland: Springer International Publishing, 2022.

[63] R. W. Robins, H. M. Hendin, and K. H. Trzesniewski, "Measuring global self-esteem: Construct validation of a single-item measure and the Rosenberg self-esteem scale," *Pers. Social Psychol. Bull.*, vol. 27, pp. 151–161, Feb. 2001.

[64] M. Rosenberg, "Society and the adolescent self-image," in *Society and the Adolescent Self-Image*. Princeton, NJ, USA: Princeton Univ. Press, Dec. 2015.

[65] R. W. Tafarodi and W. B. Swann, "Two-dimensional self-esteem: Theory and measurement," *Pers. Individual Differences*, vol. 31, pp. 653–673, Oct. 2001.

[66] J. Crocker and C. T. Wolfe, "Contingencies of self-worth," *Psychol. Rev.*, vol. 108, pp. 593–623, Jul. 2001.

[67] R. Buettner, D. Sauter, I. Eckert, and H. Baumgartl, "Classifying high and low self-esteem using a novel machine learning method based on EEG data," *Proc. Pacific Asia Conf. Inf. Syst.*, Jul. 2021, Paper 39.

[68] M. A. Burkhardt, "Spirituality: An analysis of the concept," *Holistic Nurs. Pract.*, vol. 3, pp. 69–77, May 1989.

[69] R. Gomez and J. W. Fisher, "Domains of spiritual well-being and development and validation of the spiritual well-being questionnaire," *Pers. Individual Differences*, vol. 35, pp. 1975–1991, Dec. 2003.

[70] A. Büssing, "The spiritual needs questionnaire in research and clinical application: A summary of findings," *J. Religion Health*, vol. 60, pp. 3732–3748, Oct. 2021.

[71] J. Hardt, S. Schultz, C. Xander, G. Becker, and M. Dragan, "The spirituality questionnaire: Core dimensions of spirituality," *Psychology*, vol. 03, no. 01, pp. 116–122, 2012.

[72] M. A. Almogbel, A. H. Dang, and W. Kameyama, "Cognitive workload detection from raw EEG-signals of vehicle driver using deep learning," in *Proc. 21st Int. Conf. Adv. Commun. Technol.*, 2019, pp. 1–6.

[73] A. Gupta, G. Siddhad, V. Pandey, P. P. Roy, and B.-G. Kim, "Subject-specific cognitive workload classification using EEG-based functional connectivity and deep learning," *Sensors*, vol. 21, Jan. 2021, Art. no. 6710.

[74] T. L. Tylka and N. L. Wood-Barcalow, "What is and what is not positive body image? Conceptual foundations and construct definition," *Body Image*, vol. 14, pp. 118–129, Jun. 2015.

[75] E. Mencarini, A. Rapp, L. Tirabeni, and M. Zancanaro, "Designing wearable systems for sports: A review of trends and opportunities in

human–computer interaction," *IEEE Trans. Human-Mach. Syst.*, vol. 49, no. 4, pp. 314–325, Aug. 2019.

[76] M. Gupta, T. L. T. Phan, H. T. Bunnell, and R. Beheshti, "Obesity prediction with EHR data: A deep learning approach with interpretable elements," *ACM Trans. Comput. Healthcare*, vol. 3, pp. 1–19, Apr. 2022.

[77] P. Lucena-Santos, S. A. Carvalho, M. D. S. Oliveira, and J. Pinto-Gouveia, "Body-image acceptance and action questionnaire: Its deleterious influence on binge eating and psychometric validation," *Int. J. Clin. Health Psychol.*, vol. 17, pp. 151–160, May 2017.

[78] E. McDermott et al., "The body image scale: A simple and valid tool for assessing body image dissatisfaction in inflammatory bowel disease," *Inflammatory Bowel Dis.*, vol. 20, pp. 286–290, Feb. 2014.

[79] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes-Ortiz, "A public domain dataset for human activity recognition using smartphones," in *Proc. 21th Eur. Symp. Artif. Neural Netw., Comput. Intell. Mach. Learn.*, 2013, pp. 437–442.

[80] J. R. Kwapisz, G. M. Weiss, and S. A. Moore, "Activity recognition using cell phone accelerometers," *ACM SIGKDD Explorations Newslett.*, vol. 12, pp. 74–82, Mar. 2011.

[81] A. Reiss and D. Stricker, "Introducing a new benchmarked dataset for activity monitoring," in *Proc. 16th Annu. Int. Symp. Wearable Comput.*. IEEE Computer Society, Jun. 2012, pp. 108–109.

[82] Y. Vaizman, K. Ellis, and G. Lanckriet, "Recognizing detailed human context in-the-wild from smartphones and smartwatches," *IEEE Pervasive Comput.*, vol. 16, no. 4, pp. 62–74, Oct.–Dec. 2017.

[83] D. Roggen et al., "Collecting complex activity datasets in highly rich networked sensor environments," in *Proc. 7th Int. Conf. Netw. Sens. Syst.*, Jun. 2010, pp. 233–240.

[84] D. Micucci, M. Mobilio, and P. Napoletano, "UniMiB SHAR: A dataset for human activity recognition using acceleration data from smartphones," *Appl. Sci.*, vol. 7, Oct. 2017, Art. no. 1101.

[85] K. Altun, B. Barshan, and O. Tunçel, "Comparative study on classifying human activities with miniature inertial and magnetic sensors," *Pattern Recognit.*, vol. 43, pp. 3605–3620, Oct. 2010.

[86] Data Science Chair, University of Mannheim, "Realworld human activity recognition dataset," *Dataset Activity Recognit. Res.*, 2016.

[87] O. Banos et al., "Design, implementation and validation of a novel open framework for agile development of mobile health applications," *Biomed. Eng. Online*, vol. 14, no. Suppl 2, 2015, Art. no. S6.

[88] S. Walter et al., "The BioVid heat pain database data for the advancement and systematic validation of an automated pain recognition system," in *Proc. 2013 IEEE Int. Conf. Cybern.*, Jun. 2013, pp. 128–131.

[89] M. S. H. Aung et al., "The automatic detection of chronic pain-related expression: Requirements, challenges and the multimodal EmoPain dataset," *IEEE Trans. Affect. Comput.*, vol. 7, no. 4, pp. 435–451, Oct.–Dec. 2016.

[90] G. Vavoulas, C. Chatzaki, T. Malliotakis, M. Pediaditis, and M. Tsiknakis, "The MobiAct dataset: Recognition of activities of daily living using smartphones," in *Proc. Int. Conf. Inf. Commun. Technol. Ageing Well e-Health*. Rome, Italy: SCITEPRESS - Sci. Technol. Publications, 2016, pp. 143–151.

[91] Y. Ichimaru and G. Moody, "Development of the polysomnographic database on CD-ROM," *Psychiatry Clin. Neurosci.*, vol. 53, pp. 175–177, Apr. 1999.

[92] C. Wang, T. S. Kumar, W. De Raedt, G. Camps, H. Hallez, and B. Vanrumste, "Drinking gesture detection using wrist-worn IMU sensors with multi-stage temporal convolutional network in free-living environments," in *Proc. 44th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Jul. 2022, pp. 1778–1782.

[93] B. Kemp, A. Zwinderman, B. Tuk, H. Kamphuisen, and J. Oberye, "Analysis of a sleep-dependent neuronal feedback loop: The slow-wave microcontinuity of the EEG," *IEEE Trans. Biomed. Eng.*, vol. 47, no. 9, pp. 1185–1194, Sep. 2000.

[94] N. P. Team, "The nethealth project," *Website*, 2019. Accessed: Jan. 14, 2025.

[95] B. Kemp, "Sleep-edf database expanded," *Database Rec.*, 2013. Accessed: Jan. 14, 2025.

[96] C. O'Reilly, N. Gosselin, J. Carrier, and T. Nielsen, "Montreal archive of sleep studies: An open-access resource for instrument benchmarking and exploratory research," *J. Sleep Res.*, vol. 23, pp. 628–635, Dec. 2014.

[97] T. Penzel, G. Moody, R. Mark, A. Goldberger, and J. Peter, "The Apnea-ECG database," *Comput. Cardiol.*, vol. 27, pp. 255–258, Sep. 2000.

[98] N. E. Haouij, J.-M. Poggi, S. Sevestre-Ghalila, R. Ghozi, and M. Jaïdane, "AffectiveROAD system and database to assess driver's attention," in *Proc. 33rd Annu. ACM Symp. Appl. Comput.*, Apr. 2018, pp. 800–803.

[99] K. Sharma, C. Castellini, E. L. van den Broek, A. Albu-Schaeffer, and F. Schwenker, "A dataset of continuous affect annotations and physiological signals for emotion analysis," *Sci. Data*, vol. 6, Oct. 2019, Art. no. 196.

[100] V. Markova, T. Ganchev, and K. Kalinkov, "CLAS: A database for cognitive load, affect and stress recognition," in *Proc. 2019 Int. Conf. Biomed. Innov. Appl.*, Nov. 2019, pp. 1–4.

[101] C. Y. Park et al., "K-EmoCon, A multimodal sensor dataset for continuous emotion recognition in naturalistic conversations," *Sci. Data*, vol. 7, Sep. 2020, Art. no. 293.

[102] A. Reiss, I. Indlekofer, P. Schmidt, and K. Van Laerhoven, "Deep PPG: Large-scale heart rate estimation with convolutional neural networks," *Sensors*, vol. 19, Jan. 2019, Art. no. 3079.

[103] P. Schmidt, A. Reiss, R. Duerichen, C. Marberger, and K. Van Laerhoven, "Introducing WESAD, A multimodal dataset for wearable stress and affect detection," in *Proc. 20th ACM Int. Conf. Multimodal Interaction*. New York, NY, USA, ACM, Oct. 2018, pp. 400–408.

[104] S. Koelstra et al., "DEAP: A database for emotion analysis; using physiological signals," *IEEE Trans. Affect. Comput.*, vol. 3, no. 1, pp. 18–31, Jan.–Mar. 2012.

[105] J. M. Drake, "Density-dependent demographic variation determines extinction rate of experimental populations," *PLoS Biol.*, vol. 3, Jun. 2005, Art. no. e222.