Continuous Health Monitoring on Shared Mobility Devices: A Health-eScooter Prototype

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Abstract

With the growing significance of preventive medicine, the healthcare field is developing innovative technologies to support continuous health monitoring and personalized healthcare. Therefore, we equip an eScooter with sensors for electrocardiography, photoplethysmography, and a camera for indirectly monitoring vital signs. Personal eScooters and those shared can be used for health monitoring. Combining rental identity management with biomedical data analytics allows a secure and privacy-protecting collection of personal health information from multiple rental devices. We demonstrate recordings during a ride and discuss privacy protection, cyber security, and artificial intelligence challenges. Our Health-eScooter enables individual health monitoring conveniently, unobtrusively, and mobile.

Keywords: eScooter, Shared Mobility, Health Monitoring, Artificial Intelligence, Cyber Security

1. Introduction

Continuous health monitoring enables the early detection of chronic diseases and improves treatment and outcome (Steinhubl et al., 2018). It is crucial to recognize individual changes and initialize early intervention (Capozzi and Lanzola, 2011). Private spaces such as smart homes (Wang et al., 2021), workplaces, or vehicles (Wang et al., 2020) are suitable for continuous health monitoring (Deserno, 2020). However, many individuals are not taking advantage of this emerging technology. Usage barriers include limited access to monitoring devices, lack of awareness about their importance, and concerns regarding data and privacy protection (Baig and Gholamhosseini, 2013).

To address these challenges, we built the Health-eScooter as a prototype for rental devices. In 2022, more than 10 million people used scooter sharing in Germany (Janson, 2022). Therefore, many individuals can benefit from continuous monitoring while following their daily activities.

The Health-eScooter captures vital signs during the ride and incorporates data analytics and artificial intelligence (AI), detects patterns, and generates alerts or recommendations (Rizwan et al., 2020). We address two research questions: (i) *"How to technically implement continuous health monitoring on shared mobility devices?"*, especially eScooters, and (ii) *"How to ensure data and privacy protection and cyber security?"*.

Highlighting the Health-eScooter use case, our prototype exemplifies seamless integration into daily life. By incorporating advanced monitoring technologies and sensors into a widely used mode of transportation, we create continuous health monitoring beyond traditional healthcare settings. This innovative approach enables early symptom detection, such as atrial fibrillation, and actively empowers health management. In contrast to typical smartwatches, the system performs ECG measurements for a duration exceeding 30 seconds, significantly.

With real-time data on vital signs, activity levels, and other health metrics, riders of the Health-eScooter can make informed decisions about their lifestyle, seek timely medical assistance, and make necessary adjustments to improve their overall well-being.

2. State-of-the-art

The World Health Organization (WHO) defines health as the absence of illnesses and the comprehensive perception of an individual's position.

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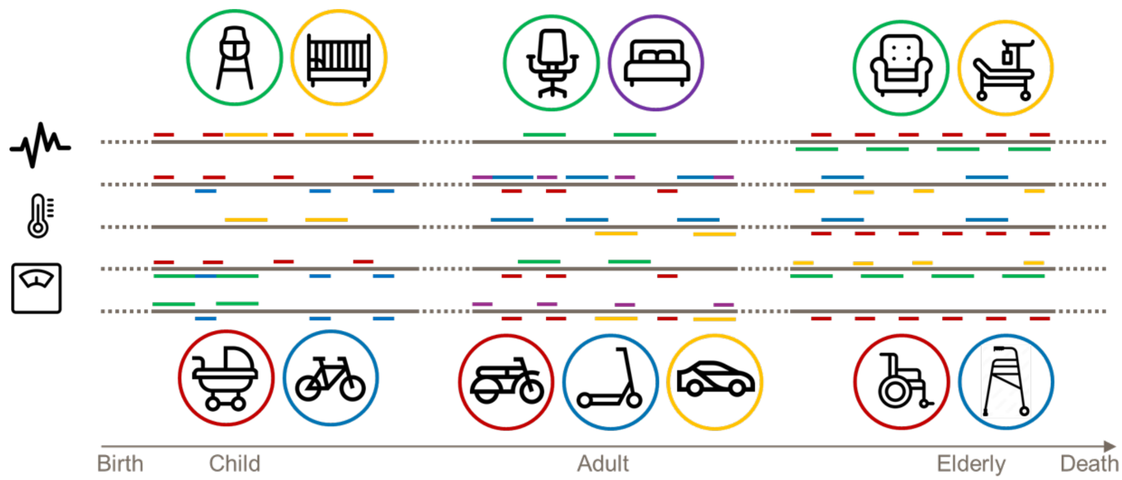

Figure 1. Continuous data recording spans the entire individual's lifetime.

The person's life is considered in the context of their culture and value system and about their goals, expectations, standards, and concerns. According to WHO, this Quality of Life (QoL) is assessed on six levels (World Health Organization, 1997):

- *Environmental*: pollution, noise, traffic, climate, but also financial resources, freedom, and the home environment;
- *Behavioral*: mobility, activities of daily living, and level of independence;
- *Physiological*: health, energy and fatigue, pain and discomfort, sleep and rest;
- *Psychological*: bodily image and appearance, feelings, self-esteem, concentration;
- *Social*: personal relationships, social support, and sexual activities;
- *Spiritual*: religion, spirituality and personal beliefs.

From these domains, we consider physiological parameters the most important for health, and their continuous monitoring is challenging. Healthcare-related personal sensors have been subject to research for more than 20 years, e.g., devices for continuous electrocardiography (ECG) (Led et al., 2004).

Durán-Vega et al. have suggested a cloud-based middleware for shared health data collection. Here, family members and caregivers of the elderly can contribute to an individual database, while the subject wears a mobile health data recorder on his wrist (Durán-Vega et al., 2019).

In recent years, continuous health monitoring has been linked to mobile devices like smartphones, which allow the processing and transmitting personal health data (Spring et al., 2013). Regarding vehicle-based data recording, concepts have been designed for health monitoring (Wang et al., 2020). For instance, camera-based imaging became a way of indirectly monitoring vital signs in vehicles (Kuo et al., 2015). Moreover, integrating sensors for health monitoring into devices such as beds (Harrington et al., 2021), armchairs (Warnecke et al., 2021), and sensor patches (Kulau et al., 2022), may complete lifelong health monitoring.

Our prototype exemplifies seamless integration into daily life. By incorporating advanced monitoring technologies and sensors into a widely used mode of transportation, we create continuous health monitoring beyond traditional healthcare settings. This innovative approach enables early symptom detection and actively empowers health management. With real-time data on vital signs, activity levels, and other health metrics, riders of the Health-eScooter can make informed decisions about their lifestyle, seek timely medical assistance, and make necessary adjustments to improve their overall well-being.

3. Lifelong health monitoring

Lifelong health monitoring encompasses an individual's life, from birth to death, and involves the comprehensive tracking of various parameters recorded with different sensors (Fig. 1). Vital signs indicate the human body's physiological function. In particular, the heart rate reflects cardiovascular health and indicates cardiac abnormalities or stress-related conditions (Chen et al., 2016).

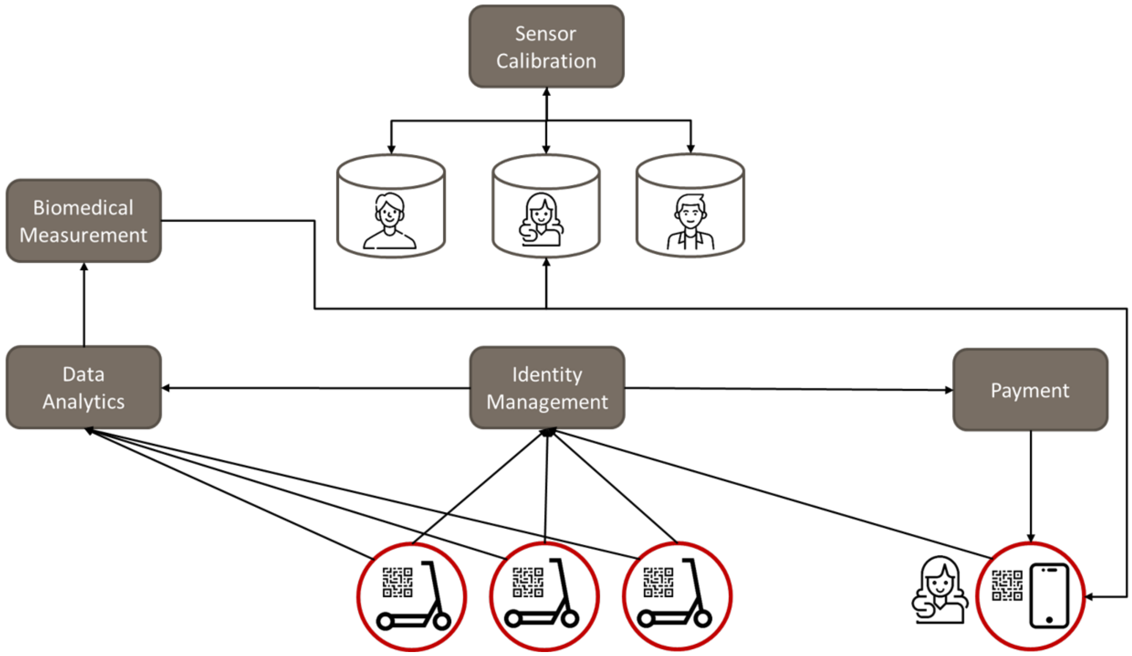

Figure 2. High-level architecture diagram from sensor calibration to payment.

The respiratory rate assesses the lung function and helps to detect respiratory distress (Loughlin et al., 2018). Regular monitoring of vital signs visualizes deviations from normal ranges, facilitates timely intervention, and prevents diseases (Evans et al., 2001). Certain icons featured in Fig. 1 can be reallocated to different life stages and additional icons can be introduced as well. Novel technology proliferates wearable devices, mobile health apps, and remote monitoring systems. These devices track and collect health-related data, including vital signs, physical activity, sleep patterns, and nutrition. Even if collected with different devices, continuous data empowers individuals to manage their health activities and facilitates decision-making and remote healthcare delivery (Steinhubl et al., 2015).

Environmental factors, such as air quality, temperature, and humidity, significantly impact health. Monitoring these environmental parameters helps to identify potential health risks, particularly for vulnerable populations. Poor air quality, for instance, exacerbates respiratory conditions (Mirabelli et al., 2018), while extreme temperatures increase the risk of heat-related illnesses (Alahmad et al., 2023). Integrating environmental monitoring into lifelong health monitoring provides a holistic perspective on the factors influencing individual well-being (Haghi et al., 2018). In addition, physical activity is a critical component of lifelong health.

Tracking activity levels and analyzing motion patterns can provide insights into individuals' overall fitness, detect sedentary behavior, and encourage adherence to exercise regimens. Wearable devices equipped with accelerometers and gyroscopes can capture movement data, allowing for quantitative physical activity assessment (Lopez et al., 2019).

While the integration of wearable devices and health apps holds immense potential for lifelong health monitoring, several challenges must be addressed: (i) seamless integration of data from different devices and apps into a cohesive and interoperable system (Dhayne et al., 2019), (ii) data security and privacy, and (iii) data analytics and appropriate alerting. The integration of ECG and PPG data into eScooter records adds a new layer of health-related information. Integrating this data with other digital phenotype data requires a sophisticated approach to store all recorded data in one application. The recorded health data can be stored within an electronic health record system with the patient's consent.

4. Health monitoring components

The high-level architecture of continuous health monitoring based on rental devices includes identity management for the rental fees and secure biomedical data collection, data analytics, and software-based sensor calibration (Fig. 2).

When a person scans the device, the smartphone app sends a unique identifier (ID) to the identity management unit, which links all biomedical measurements. The person's individual database is filled, disregarding the used vehicle.

From comparing measurement differences between users and devices, automatic compensation of offsets, and drifts is done in the cloud. The integrated sensors for health monitoring capture the biosignals, which are linked back to the rider of the rental device. We demonstrate the feasibility of the Health-eScooter use case. Companies stand to gain the advantage of offering an additional service to their customers. However, it's important to note that obtaining approval for a medical product necessitates substantiating its feasibility through comprehensive studies.

4.1. Identity management and data storage

Identity management is already implemented in the rental payment app. There are different approaches for storing health data: (i) locally on the device, (ii) in the cloud, and (iii) hybrid, combining elements of (i) and (ii). For instance, the Apple Watch tracks activity, heart rate, ECG, and other health-related parameters using a hybrid solution (Apple, 2023b). The primary storage location is the paired iPhone's Health app. Users can select comprehensive settings in the Health app to collect, share, and store their health data. Encrypted backups of the iPhone, created through iCloud, include the health data (Apple, 2023a). Synchronization via iCloud enables the secure sharing of encrypted health information across multiple Apple devices. The iCloud data is stored in an encrypted format at rest (Apple, 2023a). This solution is also applicable to the Health-eScooter. Alternatively, the data can be transferred back to a smartphone app.

4.2. Data Analytics

Continuous health monitoring is based on the analysis of biosignals. Advanced statistical methods enable fast and reliable analysis of single or multiple time series. Nevertheless, these methods only detect inter-dependencies between the time series and cause-and-effect laws, coupling the health data with known or undetected diseases (Berente et al., 2021). AI methods are more powerful and flexible but as "black boxes" difficult to comprehend, not only for developers and users but also for decision-makers (Kaur et al., 2022). Data analytics in health applications must be transparent, interpretable, understandable, and certifiable.

Moreover, data analytics in health applications must strictly follow ethical guidelines, and all electronic devices must meet data protection, privacy, and cyber security standards.

4.3. Sensor calibration

We expect offsets and different scales of the biosignals when they are recorded with different hardware devices. However, if several users use several devices, a software-based calibration can be implemented that adjusts data from one user compared to data from the other on the same device.

5. A Health-eScooter prototype

Based on an off-the-shelf eScooter (MAX G30D 2, Segway-Ninebot, Peking, China), we incorporate a sensor system (i.e., ECG, PPG, accelerometer, video) that synchronously records multiple biosignals (Fig. 3).

Figure 3. Health-eScooter prototype.

5.1. Biomedical sensors

The ECG sensor (ECG Sensor (3 x 30 cm), PLUX Biosignals, Lisbon, Portugal) records a 1-channel ECG using three electrodes attached to the handlebar. One electrode on each handlebar functions as the negative and positive electrodes, while the third serves as a voltage reference.

The ECG electrodes are printed of flexible polyurethane material (Warnecke et al., 2022). This setup accurately captures the heart's electrical activity. Furthermore, the Health-eScooter utilizes a photoplethysmography (PPG) sensor (SpO2 sensor, PLUX Biosignals, Lisbon, Portugal). This sensor employs one red (approx. 655 nm) and one infrared (approx. 940 nm) light-emitting diode (LEDs) as well as a photodiode measuring the reflected light intensity. Moreover, we measure the ground truth with three adhesive electrodes attached to the upper body as reference ECG (ECG Sensor (3 x 30 cm), PLUX Biosignals, Lisbon, Portugal). We recorded the data of six drivers.

5.2. Other sensors

Additionally, we integrate a red, green, and blue (RGB) camera (Raspberry Pi Camera, Raspberry Pi Foundation, Cambridge, UK), enabling face recognition and indirect heart rate measurements. Furthermore, it facilitates signal quality assessment, offering visual cues for the evaluation process. To capture facial landmarks of the driver (Fig. 4), we apply the face recognition engine SeetaFace from Wu et al. Wu et al., 2017. The cascade schema for face detection progressively narrows the search space. It utilizes stacked auto-encoder networks for landmark detection and a modified AlexNet for face composition. These methods enable accurate face detection, precise landmark extraction, and improved face composition. Lastly, we attach an accelerometer (Accelerometer, PLUX Biosignals, Lisbon, Portugal) to enable comprehensive motion sensing.

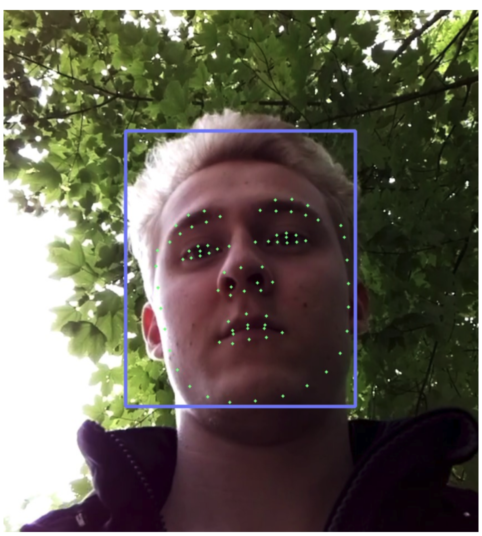

Figure 4. Face recognition.

5.3. Further hardware components

We use an external and rechargeable battery for the power supply of this sensor system.

The channel hub (BiosignalPlux Explorer, Plux Wireless Biosignals, Lisboa, Portugal) transfers via Bluetooth the ECG, PPG, and accelerometer signals to a Raspberry Pi (Raspberry Pi model B with 4 GB RAM, Raspberry Pi Foundation, Cambridge, UK). The camera has a wired connection to the Raspberry Pi.

6. Explainable AI, privacy protection, and cyber security

The convenient and unobtrusive measurement and the merging of real-time health data from human sensors, their quality-assured interpretation, and the direct embedding in control loops and automated decision-making and assistance can significantly promote quality of life, well-being, and health, but also user participation.

6.1. XAI for transparency, interpretability, and trustworthiness

Explainable AI (XAI), also known as the "white box" or "grey box," enables a better understanding of models and systems through easy interpretability and traceability, i.e., the degree to which humans understand AI decisions. XAI includes to program XAI methods, deducing user-centric guidelines and principles for XAI applications, and discussing XAI challenges and requirements (Gerlach et al., 2022). The Defense Advanced Research Projects Agency (DARPA) defines XAI as creating explainable models maintaining high predictive accuracy that enables humans to understand, trust, and use AI efficiently.

AI includes *machine learning (ML)*, which learns from data without complex rules, mainly used for pattern recognition and prediction. *Deep learning (DL)* is a subfield of ML and characterized by high accuracy and high performance, mainly used in image or speech recognition and for predicting time series. The "white/grey box" combines AI/ML/DL, human-computer interactions (HCI), and explanations from human experts in an application domain without explaining internal AI structures or algorithms in its functions. XAI models operate with algorithms and methods such as local interpretable model-agnostic explanations (LIME), Shapley additive explanations (SHAP), or explain like I am 5 (ELI5), which are different in their advantages and disadvantages w.r.t. performance and accuracy. LIME approximates AI models using interpretable models.

This model-independent technique interacts locally to understand and approximate global learning models. SHAP supports explaining models and features to build the model, presents ML forecasts based on a feature assignment, and analyzes a feature meanings distribution. SHAP clarifies predictions and global as well as local explanations.

ELI5 supports classification and regression models, computing the feature relevance based on the weights of the ML model. ELI5 is not model-independent.

Societal fears lead to discussions, especially about discrimination or unsafe behavior of AI in the sensitive healthcare area.

Security, privacy, and personnel data protection concerns about these technologies are justified because alternating misunderstandings and misinterpretations in socio-technical systems are the leading causes of undesirable behavior, hazards, accidents, and problems with acceptance. Health-eScooters using AI must be underpinned by harm avoidance, legal compliance, and technical robustness and support decision-making based on general societal views.

Hybrid Intelligence (HI) as a complement to human intellect refers to the synergistic and proactive collaboration of humans and machines to compensate for human weaknesses and augment human decision-making capabilities, e.g., anomaly detection.

Certifiability is mandatory for all health applications and requires transparency and quality assurance. This also includes ethical and legal aspects and comparability of different AI solutions regarding the same standards and compliance with laws and regulations, e.g., ISO 27001, including information security management and ethical-by-design development and operation principles. AI ethics ensures the importance of human action and oversight, societal and environmental well-being, and AI responsibility and explainability.

Explainability is essential to ethics, while ethics is not necessarily fundamental to explainability. Therefore, the extent to which health monitoring is accepted–dependent on a culture's and country's values and norms–must be clarified.

Disclosure and sharing of personal health data are uncomfortable for many customers due to the lack of trust and transparency, inhibiting the Health-eScooter's acceptance. In addition, there are concerns about cybercrime, i.e., a successful attack to compromise system integrity, and governments must set standards and guidelines for Health-eScooters. Thus, *critical success factors* include efficient government regulations, transparent privacy policies, and sufficient certifications and education.

6.2. Privacy protection of health data

Health data is arguably the most sensitive data. Moreover, protecting such data is paramount for all technical solutions connected to health.

In our given Health-eScooter scenario, we have to separate the involved parties and their respective access to the health data and the corresponding security goals. Due to space constraints, this paper cannot present a full privacy threat model. However, we would like to highlight a central privacy property which, under all circumstances, should be maintained: the operator of the Health-eScooter is only trusted to *record* the health data. However, all further actions on the data, such as permanent storage, analysis, or linking to individual users, can only be conducted out of the reach of the scooter provider due to data privacy concerns.

In our current prototype, we utilize the functionality provided by the iOS health application: a mobile app from the scooter provider is utilized to rent the scooter. This app's predominant purpose is the rental monitoring and billing of the customer's scooter usage. After the ride has concluded, the recorded health data is transferred from the vehicle to the provider's mobile app, which in turn hands this data without further processing or storage to the phone's health app in a write-only fashion. The iOS Health app handles the data securely and privately, as documented in Apple's corresponding specifications (Apple, 2023b).

More problematic is the fact that there currently needs to be more technical measures that prevent the scooter provider from covertly creating health profiles for the scooter users. In the existing implementation, the billing data in the provider's mobile app could be used to re-identify individual users and, thus, link their health data recordings into health profiles. In a future iteration of our model, we plan to investigate a complete decoupling of the billing process from the health recording. For this, it has to be prevented that the scooter provider learns the user's identity. Hence, pseudonymous billing and data recording must be introduced to the complete solution.

6.3. XAI for the Health-eScooter

We used the first heart rate data from the Health-eScooter prototype. We started investigating several AI services for cyber security, e.g., Darktrace, Deep Instinct, and Spin. Although our first Health-eScooter prototype data applicability checks are promising. Our Health-eScooter specific knowledge and know-how to (X)AI methods and tools are still limited, and further implementations and tests are necessary.

7. Results

The integrated health monitoring system captures and records biomedical signals, including ECG and PPG, and video as well as acceleration data. In this section, we delve into the comprehensive results obtained from the utilization of this system and the valuable insights it offers into an individual's health.

7.1. ECG and PPG recording

The recorded ECG data provide information on the heart's electrical activity, enabling in-depth analysis of the cardiac rhythm (Fig. 5).

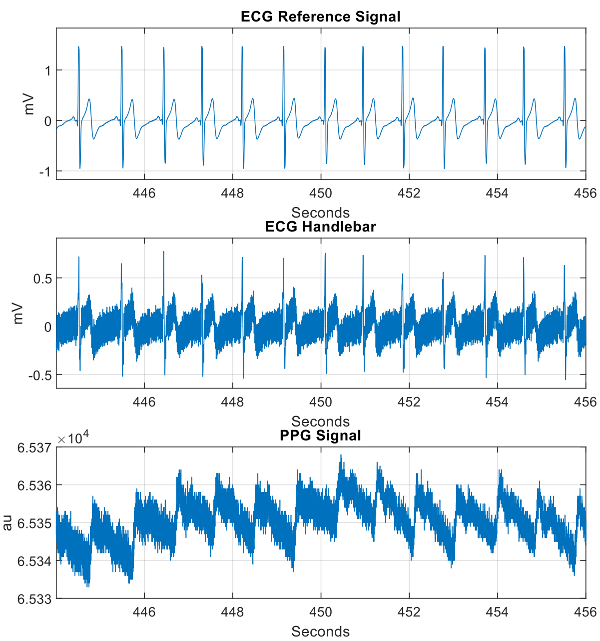

Figure 5. High SNR: ECG reference, ECG handlebar, and PPG.

Through careful examination, irregularities, arrhythmias, and potential cardiovascular conditions can be identified, contributing to timely diagnoses and appropriate interventions (Chen et al., 2016).

The PPG sensor of the integrated health monitoring system offers data regarding the cardiovascular system's functionality. By analyzing changes in blood volume within blood vessels, critical indicators such as heart rate, blood oxygen saturation levels, and pulse waveform characteristics can be derived (Castaneda et al., 2018).

The ECG and PPG signals are captured by sensors attached to the handlebar of the Health-eScooter. The quality of the recorded data and the signal-to-noise ratio depend on various factors, including the driver's movement and conductivity.

However, despite these considerations, the typical wave shape of the ECG and PPG signals remains visible without disturbances (Fig. 5).

7.2. Movement data for reliability

The acceleration sensors capture motion data to quantify the movements of the Health-eScooter and to understand its impact on the quality of biosignal recordings (Fig. 6).

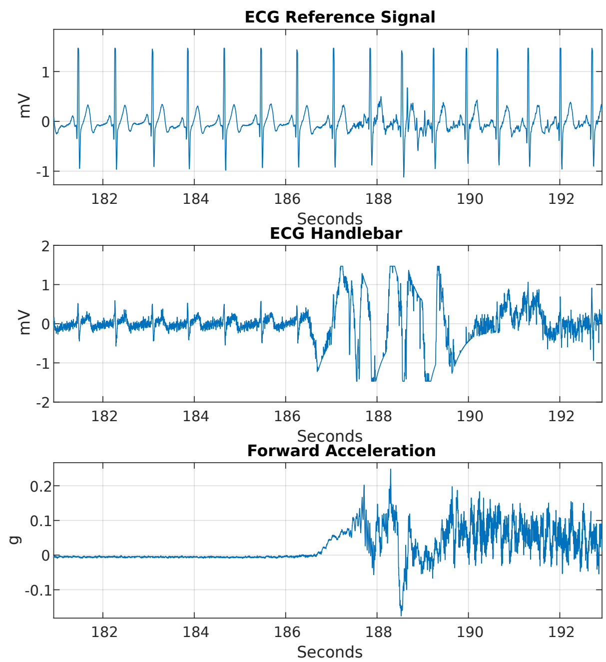

Figure 6. Low SNR during acceleration: ECG reference, ECG handlebar, and forward acceleration.

For example, in Fig. 6, the Health-eScooter accelerates at $T = 187\ s$, which directly lowers the ECG signal quality and the signal-to-noise ratio (SNR).

To effectively address this issue, we suggest weighting the biosignal's reliability according to the movement index obtained from the acceleration data.

8. Discussion, implications, and recommendations

The implementation of sensors in a vehicle-based monitoring system requires thorough planning. The prototypical systems can therefore be broken down into two major sections.

These are the on-vehicle installed hard- and software of the sensor system and the integration into adjunct systems. For the hardware components, the durability of the sensors, as well as the overall system reliability, can be a critical factor.

Especially in the case of sensor systems outfitted with sophisticated measurement devices. In addition, the power supply of a mobile, power grid-independent sensing system can limit the application's capability and thus lead to a diminished significance (Callebaut et al., 2021). Regarding the connection to downstream systems, not only the transmission technology, security, and frequency need to be considered, but also the usage of the recorded data in the implemented system (Elhoseny et al., 2018).

Considering the adjunct services of the Health-eScooter ecosystem (Fig. 2), and its variety of possible applications, a thoroughly planned implementation is inevitable to transfer the requirements manifested in the architecture onto the existing system. The Health-eScooter ecosystem can be viewed as a possible blueprint for such a system. It can be a foundation for other personal vehicles outfitted with health sensors.

The Health-eScooter serves as a valuable addition to wearable devices such as watches and fitness trackers. One of its notable advantages lies in its integrated health monitoring system, which eliminates the need for any extra effort on the part of the rider. This seamless experience is possible through the direct integration of health monitoring sensors into the eScooter's design.

Target groups are not only eScooter drivers but also, e.g., drivers of bikes, cars, trucks, or buses. Airplane pilots, who are required by law to be at least in good health, are also a prominent target group. With the Health-eScooter, in particular, younger people without any known diseases can be reached. Early detection of cardiovascular diseases or high blood pressure, especially for younger people, significantly reduces the risk of serious diseases at a young age.

Integrating scooters with advanced monitoring technologies brings numerous benefits for continuous health monitoring. However, important considerations must be addressed. Privacy and security concerns require robust encryption and adherence to privacy regulations. Efficient data management and storage mechanisms are necessary to handle the significant amount of data generated. Interoperability with existing healthcare systems can be achieved through standardized protocols and formats for data exchange.

For remote patient monitoring, sensor-equipped *Health-eScooters* enable healthcare professionals to monitor patients, e.g., with chronic conditions. By capturing real-time data, healthcare providers can detect patient health changes, allowing timely intervention and reducing the need for frequent hospital visits (Duncker et al., 2021). In particular, the combination of Health-eScooters and biomedical sensors can be integrated into telemedicine platforms, enabling remote consultations and virtual visits between healthcare providers, physicians, and patients. The benefit of real-time data transmission and exchange with healthcare professionals during virtual consultations thus enables more accurate diagnosis or better medication adjustments. The collected data can also identify patterns and trends in the biomedical data, allowing clinicians to implement targeted interventions or optimize personalized care plans and recommendations in a regulated environment (Walker et al., 2019).

The concept of our Health-eScooter also raises the question of regulatory approval if the application is intended to be used as a medical device (Baumgartner et al., 2023). According to the definitions of the American Food and Drug Administration (FDA) and the European medical devices regulation (MDR), a medical device is defined as an *instrument, apparatus, appliance, software, implant, reagent, material, or another article* that has a specific *intended use* such as diagnosis, monitoring, treatment, alleviation, and other purposes. The wide range of biosignals and health parameters, including heart rate, oxygen saturation levels, activity tracking, and others that can be monitored by the Health-eScooter opens up two possible application directions in principle.

Suppose it is intended to be used to analyze and interpret the collected data, e.g., using machine learning-based techniques to detect patterns and generate alerts or medical recommendations leading to a clinical action (diagnostic decision or modification of a therapy). In that case, the application, which consists of a hardware device with embedded software, is a medical device according to the regulatory definition. For regulatory approval, the Health-eScooter must meet the general safety and performance requirements as a medical device, as well as requirements for risk management (ISO 14971), usability (IEC 62366), software life cycle process (IEC 62304), cyber security, clinical evaluation to demonstrate clinical validity, and other requirements. However, the more likely application case is well-being and physical training support.

Even if the Health-eScooter's monitoring system detects irregular heart rhythms that could indicate atrial fibrillation, it can notify the rider and advise him to seek medical attention. The Health-eScooter does not fall within the definition of a medical device because it merely makes a recommendation. The concept of a Health-eScooter as a certified medical device is worth pursuing, but the main application will remain in the context of well-being to support health.

9. Limitations and further research

We have discussed general continuous health monitoring on shared mobility devices and have built a Health-eScooter prototype to show general applicability (Technology Readiness Level (TRL) = 4), including specific sensors, onboard micro-computers, mobile network connectivity, and monitoring software applicable to both onboard and in cloud environments. The (X)AI methods already showed general applicability for continuous health monitoring. Further research must address higher TRL for market-ready Health-eScooter products and services.

Further analyses must include low-cost sensors in standard eScooters, an interface to combine rental identity management with biomedical data protecting users' privacy, a low-cost Internet connection with sufficient upload speed, and certified software for health applications.

While we have completed our prototype research to discuss it at HICSS 2024, it will take at least three years more to develop a market-ready Health-eScooter (TRL = 7 and higher), including a real-world evaluation with eScooter and eHealth developers, producers, and operators. Further research must address specific business model development to determine who can benefit from Health-eScooter products and services investments. For efficiency, it has to be decided which data are processed onboard and which are processed in a cloud environment. Last, more specific and advanced (X)AI-driven services must be implemented for health monitoring and cyber security.

10. Conclusions

A vital strength of our integrated health monitoring system lies in its ability to merge and synergize data from multiple sources. Combining ECG, PPG, video, and acceleration data enables a comprehensive and real-time profile of an individual's health status. We explore these synergistic effects of data integration to a more accurate and holistic assessment of an individual's well-being with a Health-eScooter prototype showing applicability and efficiency for different and large target groups (TRL = 4).

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