FACULTY OF INFORMATION TECHNOLOGY AND ELECTRICAL ENGINEERING

Mohammadreza Sadeghi

SLEEPVENTION: A DATA COLLECTION AND VISUALIZATION PLATFORM FOR STUDYING SLEEP QUALITY

Master's Thesis
Degree Programme in Computer Science and Engineering
May 2025

Sadeghi M. (2025) SleepVention: A Data Collection and Visualization Platform for Studying Sleep Quality. University of Oulu, Degree Programme in Computer Science and Engineering, 56 p.

ABSTRACT

Sleep quality plays a vital role in physical health, mental well-being, and cognitive performance. Despite the increasing use of wearable devices and mobile technologies in health monitoring, there remains a lack of digital platforms specifically designed for conducting sleep-related research. This thesis introduces SleepVention, an online platform developed to address this gap by enabling the collection, visualization, and analysis of sleep data for both users and researchers. The platform supports study creation, participant management, and data sharing through integration with Fitbit application programming interfaces (APIs) and a custom-built web application using FastAPI and JavaScript.

To evaluate the platform, two studies were conducted. The first assessed user perceptions regarding the usefulness and importance of a dedicated sleep research platform. The second explored the potential relationship between smartphone addiction and sleep quality using data collected via SleepVention and Smartphone Addiction Inventory (SPAI) and Smartphone Addiction Scale-Short Version (SAS-SV) questionnaires. A total of 31 participants completed the full study process, which included connecting a Fitbit device, submitting sleep data, and responding to questionnaires.

The results revealed strong user support for the platform's purpose and features, with participants expressing a high willingness to share sleep data, particularly when incentives or personal benefits were offered. However, the findings regarding smartphone addiction and sleep quality were inconclusive; only minor differences were observed between addicted and non-addicted participants in terms of sleep duration, start time, and efficiency.

The study demonstrates the feasibility and value of an online platform for sleep research and suggests directions for future development, including support for additional wearable devices, enhanced data visualizations, improved user experience, anonymized data comparisons, AI-driven chatbot, and extended historical data access. Together, these advancements have the potential to establish SleepVention as a comprehensive and scalable tool for sleep science.

Keywords: smartphone usage, sleep tracking, Fitbit, research platform

TABLE OF CONTENTS

ABSTRACT
TABLE OF CONTENTS
FOREWORD
LIST OF ABBREVIATIONS AND SYMBOLS
1. INTRODUCTION 7
1.1. Motivation 7
1.2. Research Questions 8
1.3. Author's Contributions and the Role of Artificial Intelligence 8
2. RELATED WORK 9
2.1. Sleep and Well-Being 9
2.2. Sleep Tracking Devices 9
2.2.1. Fitbit 9
2.2.2. Oura Ring 10
2.2.3. Dreem 11
2.3. Sleep Research Platforms 11
2.3.1. National Sleep Research Resource 11
2.3.2. Open Humans 12
2.4. Relationship Between Smartphone Addiction and Sleep Quality 12
3. DESIGN 14
3.1. Application Architecture 14
3.2. User Flows and Workflows 14
3.2.1. Login and Register 15
3.2.2. Collecting Fitbit Data 16
3.2.3. Creating and Joining Studies 18
3.2.4. Downloading Participants' Data 20
3.3. Database 21
3.4. APIs 22
4. IMPLEMENTATION 24
4.1. User Interface 24
4.1.1. Technology Choices 24
4.1.2. Homepage 25
4.1.3. Login and Register 26
4.1.4. User Profile 27
4.1.5. Studies 28
4.1.6. User Data 30
4.2. Backend Server 32
4.2.1. Technology Choices 33
4.2.2. APIs 34
4.2.3. Database 35
4.3. Data Security and Privacy Measures 35
5. STUDY DESIGN 37
5.1. Study Procedure 37
5.2. Questionnaires 37

5.2.1. Sleep Research Platform Questionnaire 38
5.2.2. Smartphone Addiction Questionnaire 39
5.3. Data Analysis Approach 39
6. RESULTS 41
6.1. Participant Demographics 41
6.2. Usefulness of the Platform 42
6.2.1. Perceived Importance of Sleep Quality 42
6.2.2. Use of Sleep Monitoring Technologies 43
6.2.3. Perceived Value of a Sleep Research Platform 43
6.2.4. Willingness to Share Personal Sleep Data 44
6.3. Relationship Between Smartphone Addiction and Sleep Quality 45
6.3.1. Relationship Between Smartphone Addiction and Sleep Duration 46
6.3.2. Relationship Between Smartphone Addiction and Sleep Start Time 47
6.3.3. Relationship Between Smartphone Addiction and Sleep Efficiency 47
7. DISCUSSION 49
7.1. Findings 49
7.1.1. RQ1: How Useful and Important Is an Online Platform for Sleep Research? 49
7.1.2. RQ2: Can Smartphone Addiction Cause Poor Sleep Quality? If So, How Much Can It Affect Sleep Quality? 49
7.2. Limitations 50
7.3. Future Work 50
8. SUMMARY 52
9. REFERENCES 53

FOREWORD

I want to express my gratitude to my supervisor, Dr. Aku Visuri, for his assistance and guidance during the process of writing this thesis. He kindly and patiently helped me from defining the initial idea to development, data collection, and providing the final feedback. I also want to thank the Center for Ubiquitous Computing and the Crowd Computing group for giving me this wonderful opportunity to work and grow with them in their group.

Ultimately, I want to thank my family who always believed in me and supported me in this long journey. Without their support, this achievement would not have been possible.

Oulu, May 28th, 2025

Mohammadreza Sadeghi

LIST OF ABBREVIATIONS AND SYMBOLS

CSE	Computer Science and Engineering
API	application programming interface
SPAI	Smartphone Addiction Inventory
SAS-SV	Smartphone Addiction Scale – Short Version
RQ	Research Question
UI	User Interface
PPG	photoplethysmography
PSG	polysomnograph
PSQI	Pittsburgh Sleep Quality Index
BMI	Body mass index
NSRR	National Sleep Research Resource
NHLBI	National Heart, Lung, and Blood Institute
FAIR	Findable, Accessible, Interoperable, and Reusable
GPS	Global Positioning System
OAuth	Open Authentication
REST	Representational State Transfer
SQL	Structured Query Language
ER	Entity Relationship
HTML	Hypertext Markup Language
CSS	Cascading Style Sheets
JS	JavaScript
Navbar	Navigation Bar
HTTP	Hypertext Transfer Protocol
RegEx	Regular Expression
ORM	Object Relational Mapper
CRUD	Create, Read, Update, Delete
HTTPS	Hypertext Transfer Protocol Secure
ID	Identity Document
LLM	Large Language Model

1. INTRODUCTION

Sleep is an essential biological process that affects nearly every system in the human body. It is closely linked to physical health, emotional well-being, cognitive functioning, and overall quality of life. High-quality sleep has been associated with an improved immune system, better mood and mental health, enhanced physical performance, lower risk of chronic diseases, and a longer life span [1, 2, 3, 4]. In contrast, sleep deprivation or consistently poor sleep quality can significantly impair daily functioning and long-term health outcomes. Given its significance, sleep has become a prominent focus in public health and biomedical research.

Despite the increasing recognition of sleep's role in health, conducting sleep research remains logistically complex. Traditional methods often rely on polysomnography (PSG), the clinical gold standard for sleep measurement. However, PSG studies are typically performed in controlled laboratory environments, making them time-consuming, expensive, and inconvenient for participants. In addition to PSG, self-reported instruments such as sleep diaries and standardized questionnaires, like the Pittsburgh Sleep Quality Index (PSQI), have been widely used in sleep research to assess subjective sleep quality [5]. These tools offer an accessible way to gather participant-reported data, although they are subject to recall bias and depend heavily on user compliance.

With the advancements of wearable sleep trackers and health-monitoring devices, there is now unprecedented potential to conduct large-scale, real-world sleep studies efficiently and non-invasively. However, few platforms have fully leveraged this potential to support end-to-end research processes, including participant recruitment, data collection, data sharing, and collaborative study management.

1.1. Motivation

The idea behind this thesis arose from the realization that while various health-tracking platforms exist, none were specifically tailored to facilitate sleep research in an accessible, scalable, and user-friendly manner. Participant recruitment is often seen as a significant rate-limiting step to the implementation of research studies [6]. Researchers usually face challenges in aggregating data from multiple sources, ensuring participant engagement, and maintaining data quality across different studies. At the same time, individuals interested in improving their sleep often lack personalized, research-driven feedback mechanisms.

To bridge this gap, the SleepVention platform was developed. The goal was to create a unified system that empowers both researchers and participants by streamlining the sleep research workflow. By integrating with widely-used wearable devices such as Fitbit, SleepVention allows users to upload their sleep data, join ongoing studies, and receive visual feedback on their sleep patterns. Researchers, in turn, gain access to curated datasets and tools for managing their studies.

This work also aims to explore behavioral factors affecting sleep, specifically the role of smartphone addiction. Smartphone overuse has been consistently linked to reduced sleep duration and quality, particularly among younger demographics. Investigating this relationship in a real-world setting using wearable-tracked sleep metrics and standardized addiction questionnaires represents a novel contribution to the field.

1.2. Research Questions

To support the objectives and scope of this thesis, two primary research questions were formulated:

RQ1: How useful and important is an online platform for sleep research?

RQ2: Can smartphone addiction cause poor sleep quality? If so, how much can it affect sleep quality?

These questions form the basis for both the platform evaluation and the empirical study carried out using SleepVention. The first question focuses on assessing the practical utility and perceived value of the system. The second aims to contribute to the growing body of research on digital behaviors and sleep by examining the impact of smartphone overuse using sleep tracking data and SPAI and SAS-SV scales.

1.3. Author's Contributions and the Role of Artificial Intelligence

The research presented in this thesis was conducted independently by the author, including the design, implementation, data collection, analysis, and writing. The SleepVention platform was fully developed by the author, encompassing both the frontend and backend systems, as well as the integration with Fitbit APIs and the creation of user workflows and data pipelines.

Artificial intelligence tools were used as supportive resources during the thesis process. Grammarly was utilized to check spelling and grammar throughout the writing of the manuscript. ChatGPT was used for revising parts of the literature, formatting LaTeX sections, and assisting with writing code components of the platform, such as implementing API endpoints, database operations, and user interface (UI) logic. However, no part of the thesis text was generated by ChatGPT or any other language model. All academic writing, analysis, and content creation were carried out by the author.

2. RELATED WORK

2.1. Sleep and Well-Being

Sleep is a fundamental biological process that plays a vital role in physical, cognitive, and emotional functioning. Healthy sleep is increasingly recognized as a cornerstone of public health, with insufficient or poor-quality sleep being associated with a broad spectrum of health risks, including cardiovascular disease, metabolic disorders, depression, and impaired immune function [7]. The American Thoracic Society emphasizes the need for societal-level strategies to promote sleep health, suggesting that sleep should be treated as a pillar of health alongside nutrition and physical activity.

Despite its importance, sleep remains an often overlooked and under-addressed public health issue. Reports from the Institute of Medicine have described sleep disorders and sleep deprivation as an unmet public health problem, citing insufficient awareness, underdiagnosis, and limited research funding as contributing factors [8]. These systemic gaps have led to widespread negative outcomes, particularly in occupational and educational settings, where sleep loss is linked to reduced performance, increased error rates, and higher accident risk.

The economic and productivity consequences of chronic short sleep are also well documented. Ohlmann et al. estimate that inadequate sleep significantly contributes to healthcare costs and lost workdays, and has measurable effects on employee performance and safety [9]. As such, promoting sleep as a health behavior may serve not only individual well-being but also broader economic and societal outcomes.

Public health initiatives have begun to respond to this need by framing sleep as a modifiable behavior within wellness promotion efforts. Programs aimed at raising awareness and encouraging behavioral change around sleep are increasingly emphasized by agencies such as the Centers for Disease Control and Prevention [10]. These initiatives advocate for policy changes, environmental interventions, and individual education to support improved sleep habits at the population level.

Advances in digital health and web-based platforms have enabled researchers to study sleep behavior at scale. For instance, Althoff et al. demonstrated how online interaction patterns can serve as passive indicators of sleep and cognitive performance, providing new avenues for monitoring and intervention [11]. These methods highlight the potential of scalable, data-driven approaches to understanding and enhancing sleep in real-world contexts.

2.2. Sleep Tracking Devices

2.2.1. Fitbit

Fitbit is one of the most widely used consumer-grade sleep tracking devices available in the market. These wrist-worn devices employ accelerometry and photoplethysmography (PPG) sensors to estimate sleep parameters such as total sleep time, sleep stages, and sleep efficiency. Fitbit's popularity stems not only from its wide product availability and affordability [12] but also from its relatively strong performance in sleep tracking compared to other commercial wearables [13].

Research has shown that Fitbit devices perform reasonably well when compared to polysomnography (PSG), the clinical gold standard for sleep assessment. For instance, in a systematic review and meta-analysis, Haghayegh et al. reported that Fitbit wristbands showed acceptable levels of agreement with PSG for total sleep time and sleep efficiency, although stage-specific classification (such as light or deep sleep) was less accurate [14]. Similarly, Liang and Chapa-Martell found that Fitbit devices demonstrate modest accuracy in detecting sleep stage transitions, though performance varied with user-specific factors such as age, BMI, and gender [15].

Further evidence from field studies supports the viability of using Fitbit in research contexts. Kuosmanen et al. compared several consumer sleep tracking devices and found Fitbit to be suitable for longitudinal studies due to its usability, cost-effectiveness, and acceptable reliability for general sleep measures [16]. Additionally, Menghini et al. evaluated the Fitbit Charge 3 model against PSG in adolescents and found good agreement for total sleep time and sleep onset latency, supporting its use in younger populations [13].

Despite its widespread use, several reviews have emphasized the importance of cautious interpretation when using Fitbit data for scientific or clinical purposes. Ibáñez et al. pointed out that validation protocols and algorithms are often proprietary and non-transparent, which limits reproducibility and scientific rigor [17]. Nonetheless, given their widespread adoption and reasonable performance for general sleep metrics, Fitbit devices remain valuable tools for sleep research in naturalistic settings.

2.2.2. Oura Ring

The Oura Ring is a commercially available, multisensor sleep tracking device worn on the finger, offering a compact and unobtrusive form factor. It uses a combination of photoplethysmography (PPG), body temperature sensors, and a 3D accelerometer to monitor sleep-wake patterns, heart rate, and motion. The integration of these data streams allows the device to estimate sleep duration and stages with high resolution [18].

Validation studies have investigated the Oura Ring's performance against gold-standard sleep assessment methods such as polysomnography (PSG). De Zambotti et al. conducted one of the earliest comparative studies and found that the Oura Ring showed high agreement with PSG in detecting total sleep time and sleep onset latency, though it underestimated wake after sleep onset and overestimated deep sleep duration [19]. Similar results were reported by Chee et al., who validated the device over multiple nights in adolescents and observed strong concordance with PSG and research-grade actigraphy for sleep timing, with some limitations in stage classification accuracy [20].

Further evidence supports the Oura Ring's application in behavioral and field research contexts. Roberts et al. examined multisensor wearables including the Oura Ring and found that heart rate combined with motion data improved sleep detection relative to actigraphy alone. Their findings indicated that the Oura Ring, by leveraging both cardiovascular and movement data, provides enhanced precision in identifying sleep onset and duration [21]. Additionally, machine learning-based approaches applied to the Oura Ring's data pipeline have been shown to improve sleep staging accuracy, further aligning consumer-grade measurements with clinical standards [18].

Overall, the Oura Ring demonstrates sufficient accuracy and reliability for use in both personal and research applications, particularly in naturalistic environments where less obtrusive monitoring is desirable.

2.2.3. Dreem

The Dreem headband is a neurotechnology-based sleep tracking device designed to monitor sleep with a focus on brain activity. Unlike most consumer-grade wearables that rely primarily on motion and heart rate data, Dreem incorporates dry electroencephalography (EEG) electrodes to capture brain signals directly. This allows for more precise sleep staging and signal resolution, particularly in detecting sleep onset and transitions between sleep stages.

Arnal et al. conducted a comprehensive validation study comparing the Dreem headband to gold-standard polysomnography (PSG) across multiple nights. Their findings indicated that Dreem's automatic sleep staging algorithm demonstrated high concordance with expert-scored PSG data, especially for total sleep time, sleep onset latency, and duration in non-rapid eye movement (NREM) sleep stages. The EEG signal quality acquired from the headband was deemed reliable for both research and clinical screening applications [22].

In field applications, the Dreem headband has also been evaluated alongside other consumer-grade devices. A comparative study by Kuosmanen et al. included Dreem in a field deployment context and noted that while it required more initial setup and user familiarity than wrist-based trackers, it provided superior granularity in sleep stage classification. This trade-off between precision and usability positions Dreem as a suitable tool for longitudinal or laboratory-informed studies where EEG-grade data are essential [16].

2.3. Sleep Research Platforms

2.3.1. National Sleep Research Resource

The National Sleep Research Resource (NSRR) is a publicly accessible data-sharing platform developed to support sleep research by providing comprehensive, de-identified datasets from various clinical studies [23]. Funded by the National Heart, Lung, and Blood Institute (NHLBI), the NSRR aims to accelerate scientific discovery by offering a centralized repository of sleep-related data, including polysomnography (PSG) recordings and associated clinical information [24].

One of the key features of the NSRR is its commitment to the FAIR principles—making data Findable, Accessible, Interoperable, and Reusable. This approach facilitates data sharing and collaboration among researchers, enabling the integration of diverse datasets and promoting reproducibility in sleep research [25].

The NSRR has been instrumental in large-scale studies, such as the characterization of sleep spindles in over 11,000 individuals, which provided insights into the genetic and developmental aspects of sleep architecture [26]. Additionally, the resource supports the development and validation of computational tools, including algorithms for automated sleep staging and analysis of sleep disorders [27].

By aggregating and harmonizing data from multiple cohorts, the NSRR serves as a vital infrastructure for advancing our understanding of sleep and its impact on health, offering researchers the tools and data necessary to explore complex questions in sleep medicine.

2.3.2. Open Humans

Open Humans is a community-based platform designed to facilitate participant-centered research and personal data exploration [28]. It enables individuals to aggregate, manage, and share their personal data from various sources, including genetic data, wearable activity monitors, Global Positioning System (GPS) location records, and continuous glucose monitors. This approach empowers participants to contribute to research projects actively and promotes transparency and autonomy in data sharing decisions [29].

The platform addresses the challenges associated with merging data streams from diverse sources and the ethical considerations of personal data sharing. By providing tools and infrastructure that support data portability and interoperability, Open Humans fosters an environment where both academic and citizen scientists can collaborate effectively. The platform's modular architecture allows for the development of diverse projects, ranging from health-related studies to explorations of personal behavior patterns, thereby broadening the scope and impact of participatory research [29].

In the context of sleep research, Open Humans offers the potential to collect and analyze data from wearable devices that monitor sleep patterns. By integrating such data with other personal health information, researchers can gain deeper insights into sleep behaviors and their correlations with various health outcomes. This participant-driven model not only enhances the richness of the data collected but also ensures that individuals retain control over their personal information, aligning with ethical standards and promoting trust in research endeavors [29].

2.4. Relationship Between Smartphone Addiction and Sleep Quality

The widespread adoption of smartphones has introduced new challenges to sleep health, particularly in the context of behavioral addictions. A growing body of literature highlights a significant association between problematic smartphone use and poor sleep quality across diverse populations.

Demirci et al. investigated this relationship among university students and found that higher smartphone addiction levels were significantly associated with poorer sleep quality, as well as increased depression and anxiety symptoms [30]. Their study emphasized the bidirectional nature of this interaction, suggesting that smartphone addiction could be both a cause and a consequence of impaired sleep.

Further supporting these findings, an analysis by Yank et al. revealed that excessive smartphone use was linked to disrupted sleep patterns and delayed bedtimes, particularly among younger individuals and those reporting higher psychological distress [31]. The authors suggest that night-time smartphone usage may delay circadian rhythm synchronization and reduce overall sleep duration.

To measure the behavioral dimensions of smartphone use, validated instruments such as the Smartphone Addiction Inventory (SPAI) [32] and the Smartphone Addiction Scale – Short Version (SAS-SV) [33] have been widely employed. These tools assess symptoms including compulsive usage, withdrawal, and interference with daily life, offering robust indicators of maladaptive smartphone behavior.

Overall, the literature demonstrates a consistent and negative correlation between smartphone addiction and sleep quality. While the causal mechanisms remain complex and multifaceted, the evidence points toward the necessity of addressing smartphone overuse as part of broader sleep health interventions.

3. DESIGN

This chapter presents the design of the SleepVention platform, developed as a web-based application to support sleep research. The design process was guided by goals of accessibility, usability, and extensibility. In the following, the architectural structure, user interaction flows, database schema, and API interface are discussed in detail.

3.1. Application Architecture

The SleepVention platform follows a client-server architecture, a standard model for modern web applications. In this architecture, the frontend (client) is responsible for rendering the user interface and managing user interactions, while the backend (server) handles business logic, data processing, and interactions with external services such as Fitbit APIs.

RESTful APIs are used for communication between the frontend and backend. This design ensures modularity and separation of concerns, which improves maintainability and scalability. The frontend is implemented using standard web technologies (HTML, CSS, JavaScript), while the backend is developed using the FastAPI framework and SQLite database, with SQLAlchemy as the Object-Relational Mapper (ORM).

Figure 1 shows the high-level client-server model and the way client and server communicate. In this model, users interact with the frontend in their browsers and the frontend communicates with the backend to request data or perform operations. The backend, in turn, accesses the database or external APIs (e.g., Fitbit) to fulfill these requests and return the appropriate responses.

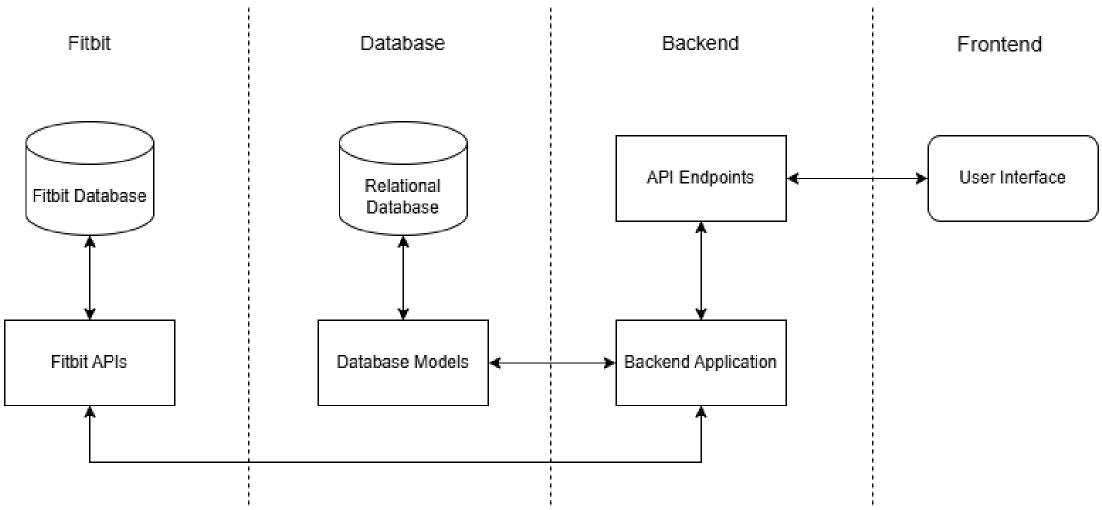

Figure 1. High-level application architecture

3.2. User Flows and Workflows

This section outlines key user flows that define how participants and researchers interact with the platform. Each functionality was designed with simplicity and ease-of-use in mind to encourage participant engagement and researcher efficiency. The main functionalities of the system were decided from the beginning of the project, but after having regular meetings and collecting feedback and insights, some changes has been made in the details or implementation of the system.

3.2.1. Login and Register

The most initial functionality of the SleepVention platform is login and registration. Without authentication, users will not get access to the key functionalities like creating a study, joining a study, upload their data, view their data, and so on. An unauthenticated user can only view the public studies on the website without the ability of joining them.

As pictured in Figure 2, upon visiting the platform, users can either log in with existing credentials or register a new account. Registration requires a valid email address, a unique username, and a secure password. Client-side validation ensures proper formatting (e.g., for email and password strength) before sending data to the backend. The backend verifies the uniqueness of the username and email and then adds the user to the database. Additional demographic information—such as age, gender, height, weight, and nationality—can optionally be added to enhance research data granularity.

Later on, in the development process, it was decided to add another page to get the user's personal information, like nationality, sex, age, height, and weight. But since it wasn't a part of the initial design, it is not included in this workflow.

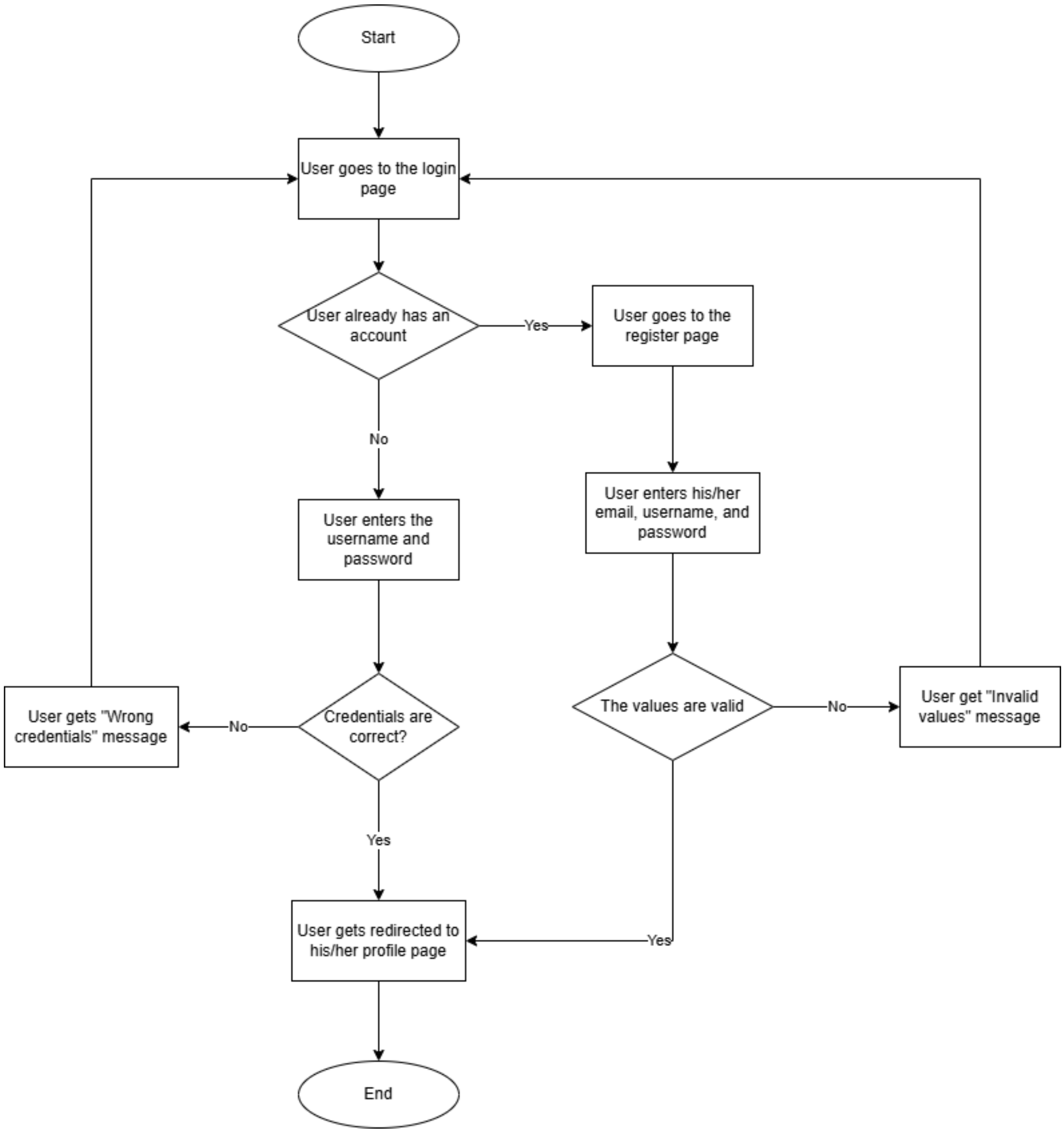

Figure 2. Login/Register workflow

3.2.2. Collecting Fitbit Data

A core feature of SleepVention is automatic sleep data collection via the Fitbit API. In the first use, participants are asked to authenticate with their Fitbit accounts through cc (OAuth). Once authenticated, the backend stores the access tokens and fetches new data each time the user views the page. Figure 3 shows a complete workflow of the data collection process in SleepVention.

Collected data includes sleep duration, efficiency, heart rate, and activity metrics. These are stored in structured tables in the backend and displayed in the user interface through tables and charts.

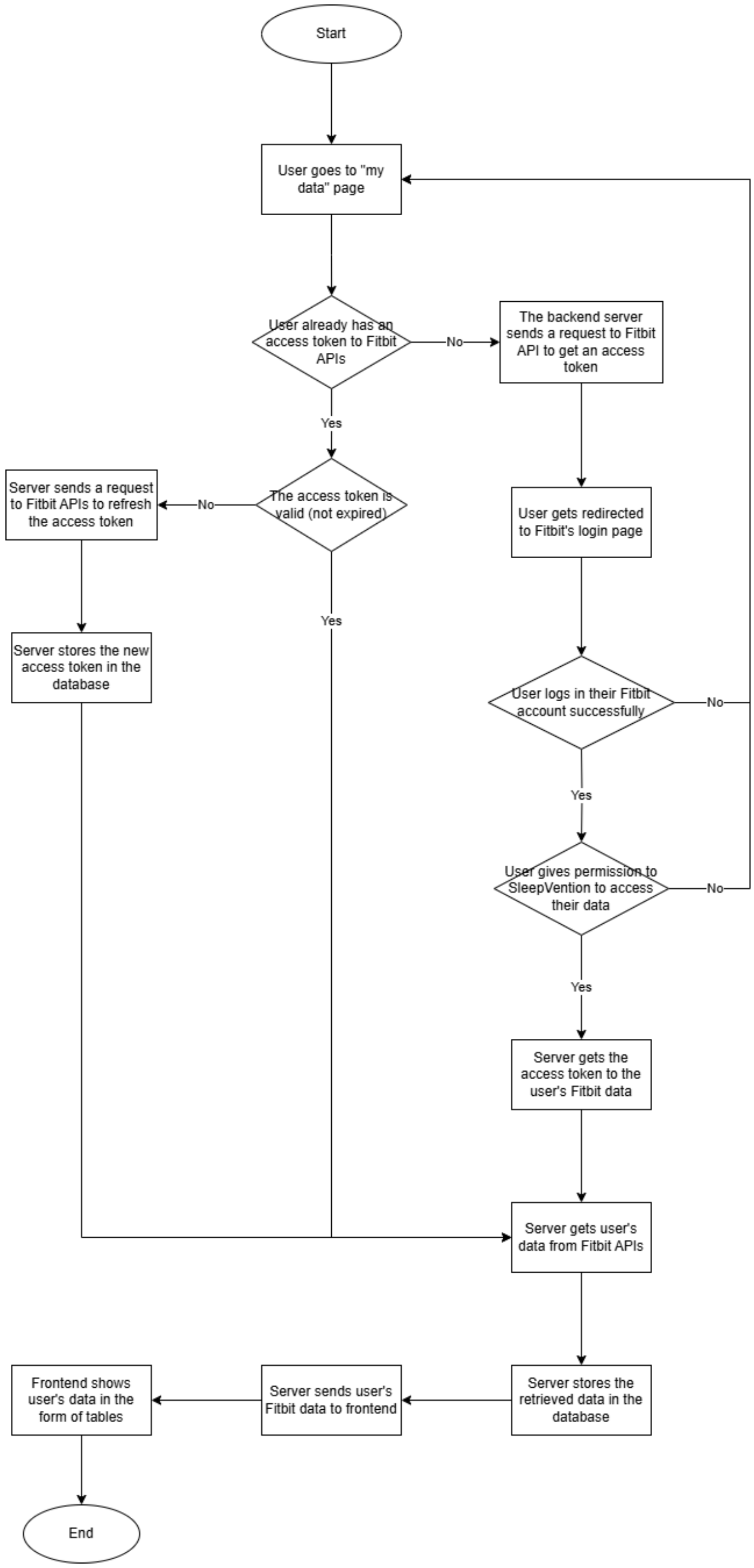

Figure 3. Data collection workflow

3.2.3. Creating and Joining Studies

Researchers can create studies by specifying a name, description, consent form link, and visibility (public or private). Viewing public studies does not require authentication, but for private studies, it does. Users can join public studies directly or by accepting study invitations sent via the platform.

Invitations are managed through a built-in messaging system. When a participant receives an invitation, they can review the study details and must view the consent form before joining. Figure 4 and Figure 5 show a high-level workflow of creating and joining a study in SleepVention.

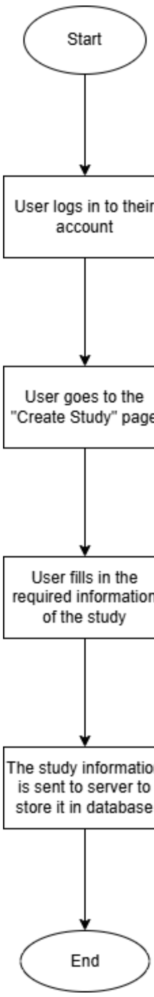

Figure 4. Creating study workflow

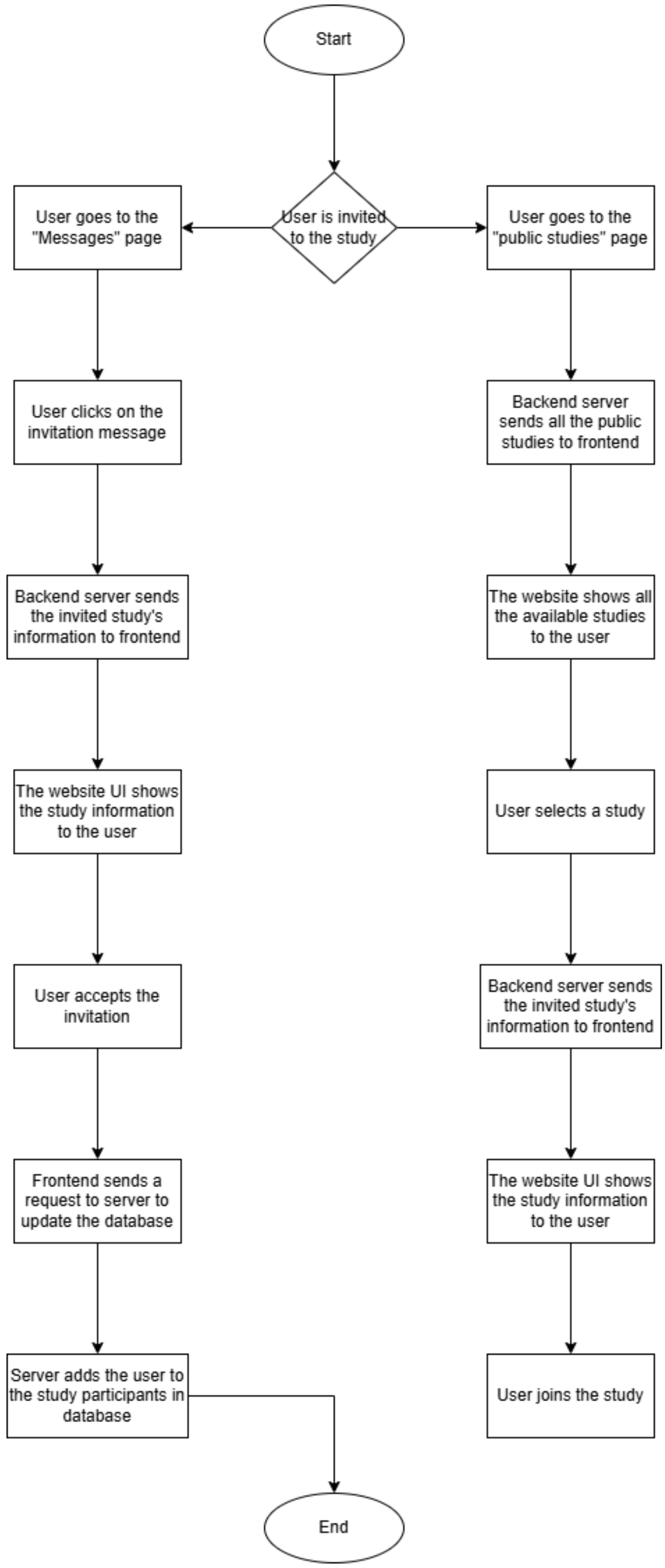

Figure 5. Joining study workflow

3.2.4. Downloading Participants' Data

Researchers can export data from their studies in CSV format for offline analysis. After careful consideration, the CSV format was chosen to ensure compatibility with a wide range of data analysis tools. Figure 6 shows the high-level workflow for downloading the data of study participants as the study creator.

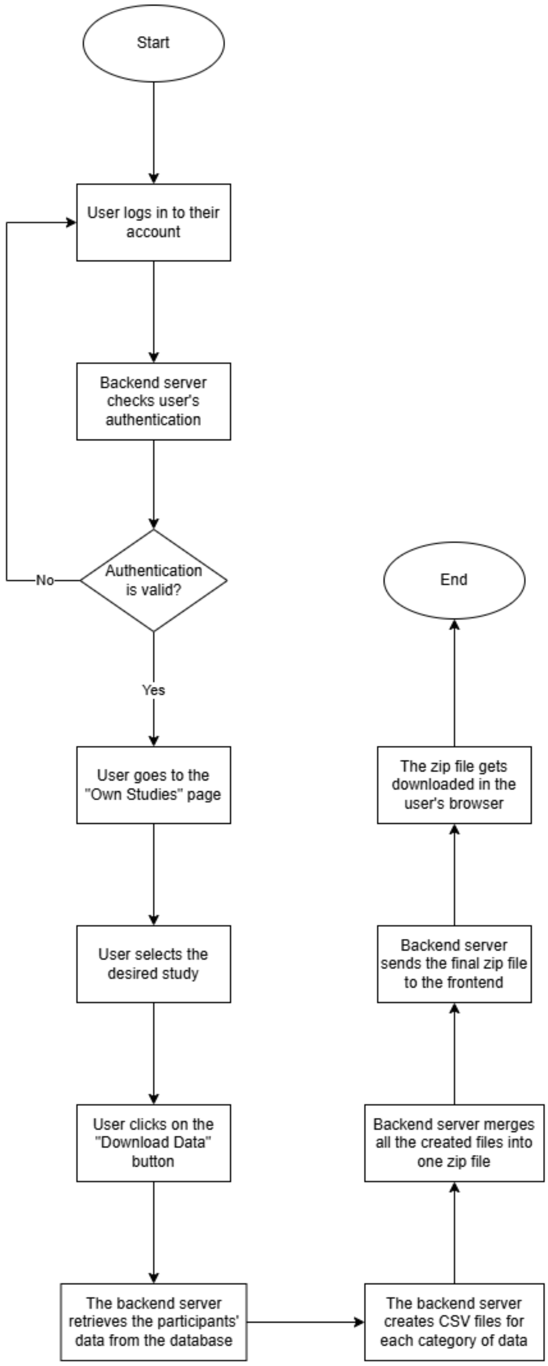

Figure 6. Login/Downloading study participants' data workflow

3.3. Database

This section explains the database design of the platform. The database design represented here follows the Structured Query Language (SQL) structure. This choice was made because all the data in the system, including users' information, studies, and Fitbit data, has a structured schema without any long unstructured text.

A total of 15 tables is designed to handle data interactions in SleepVention. Figure 7 outlines the entity-relationship (ER) diagram of the tables.

Figure 7. Database tables diagram

3.4. APIs

RESTful APIs are used for communication between the client and server in the SleepVention project. The Representational State Transfer (REST) architecture style for APIs was made to address issues with standardization over HTTP. The main constraints for a REST API include a separate server-client architecture, stateless transfers where each request holds all data needed to understand and complete it, cacheable responses, a uniform interface across coding languages where the client receives a representation of a resource (not the resource itself), and a layered architecture where clients are unaware of which server processes their request. Interface uniformity encompasses resource discovery, identification, descriptions, manipulation of said resources, and hypermedia as the engine of application state [34].

Resources available through the REST API are mostly queried from the database for each HTTP request. In this case, any data can undergo four distinct operations: create, read, update, and delete, forming the acronym CRUD. CRUD operations map to HTTP methods: POST for creating, GET for reading, PUT for updating, and DELETE for deleting a persistent resource. To implement these functions to access the database, an HTTP server framework is needed; in this case, FastAPI was selected. Easy prototyping, development, and data validation are the most important aspects of choosing FastAPI for this project.

The platform's backend exposes a comprehensive set of RESTful APIs. These endpoints allow clients to perform operations such as user authentication, data upload, study creation, and participant management. Table 1 outlines the complete set of APIs designed for this platform.

Table 1. REST API Endpoints Used in the Thesis Project

Endpoint	**Method**	**Description**
`/register/`	POST	Registers a new user and returns an authentication token.
`/login/`	POST	Authenticates a user and returns a token.
`/get_profile/`	GET	Fetches the profile information of the authenticated user.
`/profile/`	PUT	Updates the profile information of the user.
`/get_home/`	GET	Checks if the user is authorized and returns status.
`/get_explore/`	GET	Returns user sleep logs and average sleep data.
`/get_about_us/`	GET	Checks authorization for about-us content.
`/get_mydata/`	GET	Fetches all Fitbit-related data for the current user.
`/fitbit-authenticate`	GET	Handles Fitbit OAuth callback and stores tokens.

(continued on next page)

Endpoint	Method	Description
/fitbit_authenticating_url	GET	Generates and returns Fitbit authentication URL.
/data_file/	POST	Uploads a user-provided data file.
/get_data_privacy/	GET	Fetches current data privacy settings.
/data_privacy/	PUT	Updates the user's data privacy settings.
/study/	POST	Creates a new study (currently disabled).
/study/{study_id}/	PUT	Edits an existing study by ID.
/get_own_studies/	GET	Returns studies created by the user.
/get_participated_studies/	GET	Returns studies the user is participating in.
/get_study/{study_id}/	GET	Fetches detailed data for a specific study.
/study/{study_id}/	DELETE	Deletes a study by ID.
/study/{study_id}/invite/	POST	Invites a user to a study.
/get_invitations/	GET	Returns invitations received by the user.
/invitation/{study_id}/	DELETE	Deletes an invitation for a study.
/invitation/{study_id}/	PUT	Accepts an invitation to a study.
/join_study/{study_id}/	POST	Joins a study using an invitation and participant identifier.
/get_study/{study_id}/data/csv/	GET	Returns all study data for download as a ZIP file.
/get_studies/public/	GET	Returns all public studies available to unauthenticated users.
/check_authorization/	GET	Checks if a user is currently authorized.

4. IMPLEMENTATION

This chapter presents implementations of software components developed during the thesis project for the SleepVention platform, alongside the data security and privacy measures. The components include the web user interface and the backend server. For each component, the technology choices, main functionalities, and the interaction with other components are explained in detail.

4.1. User Interface

This section details the implementation of SleepVention's user interface and shows how it interacts with the user and the backend server. This user interface is implemented as a web application with HTML, CSS, JavaScript, and Bootstrap. The frontend operates as a multi-page web application that fetches the UI and content of each page using REST APIs from the backend server whenever the current page changes. Most of the UI elements in the frontend application are built using Bootstrap's standard, predesigned components. The reason behind these technology choices is discussed in detail in the following section.

4.1.1. Technology Choices

The user interface (UI) of the web application was developed using HTML, CSS, JavaScript, and Bootstrap. These technologies were chosen due to their widespread use, flexibility, ease of integration, and support for responsive and accessible design.

HTML provides the structural foundation for web content and is the standard markup language used across the web. It ensures that the application is accessible and compatible with all modern browsers, making it an essential choice for developing content-rich web interfaces.

CSS was used to define the visual presentation of the application. With the separation of content (HTML) and style (CSS), the UI design remains modular and easier to maintain. CSS enables precise control over layout, typography, and visual effects, which are crucial for ensuring a consistent and aesthetically pleasing user experience.

JavaScript was employed for handling client-side interactivity, such as dynamic content updates, form validation, and API calls to the backend server. JavaScript's event-driven architecture and compatibility with all major browsers make it the standard for creating interactive web applications [35]. It was important for us to choose the simplest and easiest-to-use technology for handling the UI interactions. And since SleepVention's UI is a simple and small-scale web application, plain JavaScript, also known as Vanilla JavaScript (Vanilla JS), is the best choice for this project compared to well-known and widely used frameworks like Angular and React [36, 37].

To accelerate UI development and ensure mobile responsiveness, Bootstrap was integrated into the project. Bootstrap is a popular open-source CSS framework developed by Twitter, which provides a set of pre-styled components and grid systems.

It significantly reduces development time while ensuring responsive design principles are followed [38]. This was particularly beneficial, because the main factor for desiging the UI was to create a standard and simple UI that is compatible with all desktop devices, in the quickest way possible, which could be achieved with Bootstrap.

The combination of these technologies aligns with common best practices in modern web development, and their open-source nature and strong community support ensure long-term maintainability and scalability of the application.

4.1.2. Homepage

The homepage serves as the primary entry point for all users. It is accessible to both authenticated and unauthenticated users and primarily displays a list of publicly available studies. This allows new visitors to explore ongoing research without requiring immediate registration. Figure 8 shows the UI of the homepage.

At the top of the homepage, a navigation bar (navbar) provides quick access to other sections of the platform. For unauthenticated users, the navbar includes links to the homepage, explore page, login page, and "About Us" section. Once a user logs in, the navbar dynamically updates to provide access to additional features, such as the user's profile, their studies, and uploaded data. The nav-bar after authorization can be seen in Figure 11.

The structure and design of the homepage were guided by usability principles aimed at reducing cognitive load for first-time visitors. By presenting essential content clearly and concisely, the interface encourages user exploration and lowers the barrier to participation. All studies shown on the homepage are publicly accessible, but joining them requires user authentication.

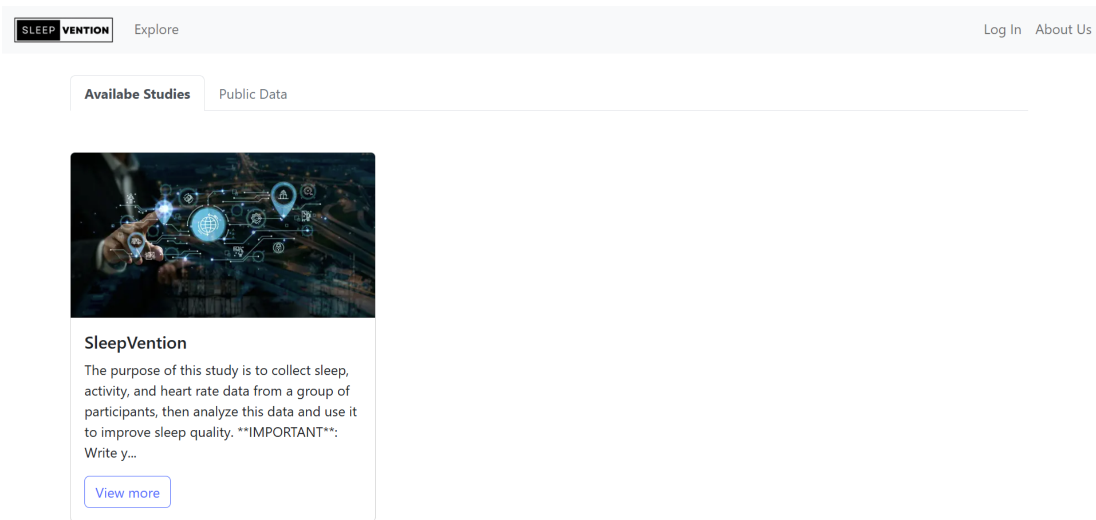

Figure 8. SleepVention homepage

4.1.3. Login and Register

Authentication is a fundamental part of the platform's design, enabling secure access to features such as profile management, data upload, and participation in studies. The login and registration pages were implemented using HTML and JavaScript, with user input validated on the client side before being submitted to the backend. Figure 9 and Figure 10 show the UI of the login and register pages.

For login, users are asked to enter their registered username and password. This information is sent to the server, where it is validated against the stored credentials in the database. Upon successful authentication, the server responds with an HTTP 200 status code and generates an access token that is used to authorize subsequent requests. If authentication fails, the server returns a 400 status code with an appropriate error message.

The registration process requires users to provide a unique username, a valid email address, and a password that meets minimum security criteria. These criteria include a combination of uppercase and lowercase letters, numbers, and a minimum character length to ensure password strength. Input validation is performed using JavaScript, including regular expression (RegEx) checks for email format and password complexity.

Once validated, the user information is submitted to the backend, where it is checked for uniqueness. If the username and email are not already in use and the input meets all validation rules, a new account is created and stored in the database. Following registration, users are redirected to a profile setup page to optionally enter demographic information such as age, nationality, gender, height, and weight.

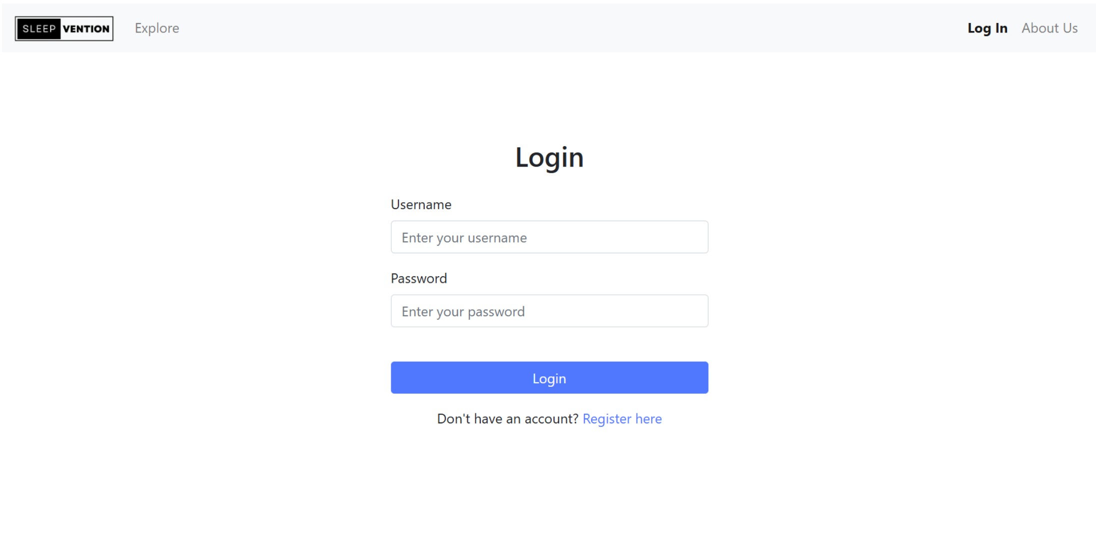

Figure 9. SleepVention login page

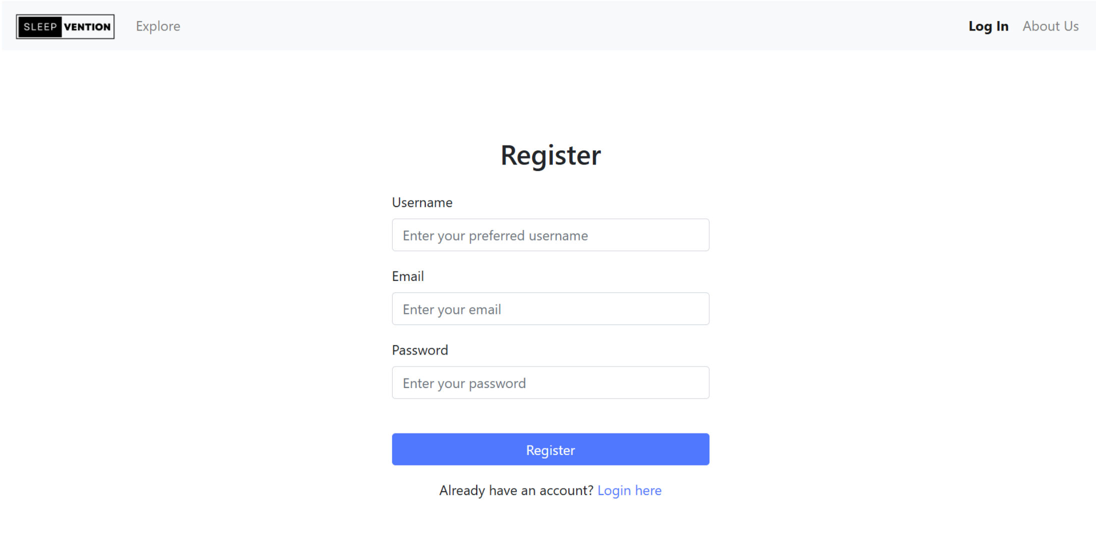

Figure 10. SleepVention register page

4.1.4. User Profile

After successful registration, users are redirected to the profile setup page (Figure 11), where they can enter optional demographic information, including nationality, date of birth, gender, height, and weight. While these fields are not mandatory, they can enhance the quality and contextual relevance of the data collected for research purposes.

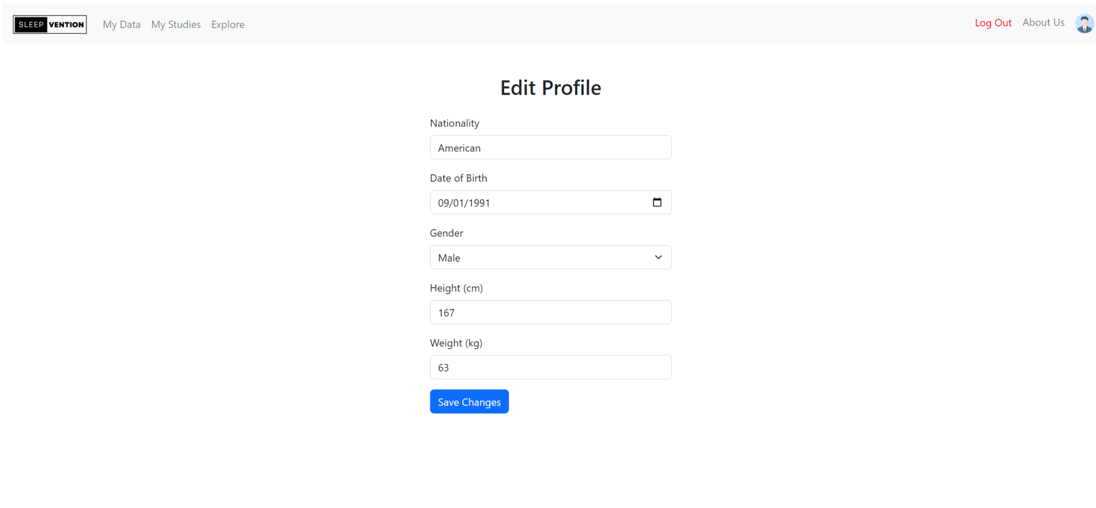

Figure 11. SleepVention edit profile page

The profile page serves as a centralized hub for users to view and manage their personal information and study-related interactions. As outlined in Figure 12, on the left side of the screen, users can review their saved demographic data, which can be updated at any time through the "Edit Information" button. On the right side of the page, users can access system-generated messages, including invitations to participate in private studies.

Each invitation message includes the study title, a brief description, and action buttons to either view the study or reject the invitation. To promote informed consent and encourage data transparency, the platform requires users to visit the study page and read the associated consent form before accepting any invitation. Direct acceptance from the message panel is intentionally disabled to ensure this step is not bypassed.

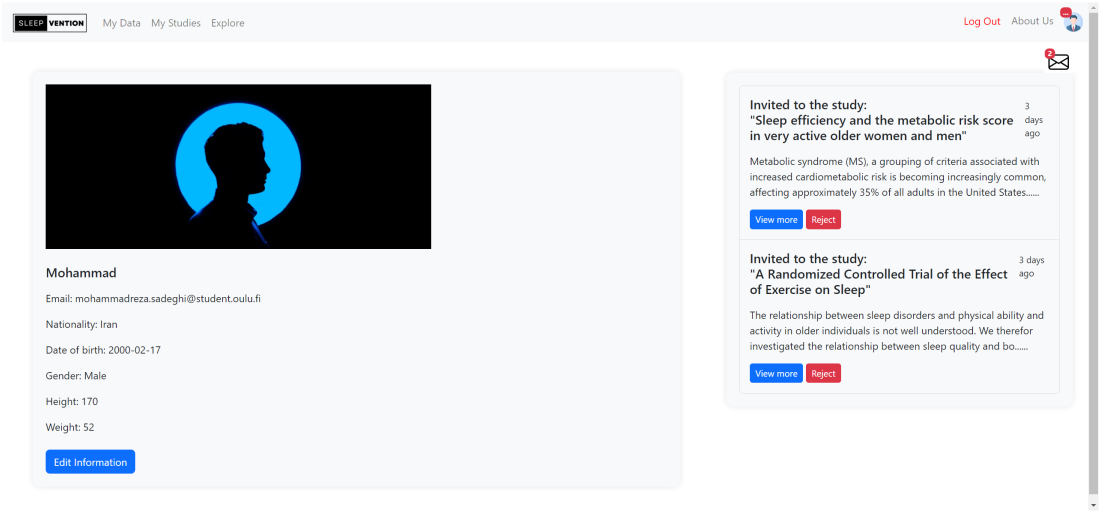

Figure 12. Messages in the profile page

4.1.5. Studies

A core feature of SleepVention is the ability for users to participate in or manage research studies. The "My Studies" page, outlined in Figure 13, allows users to view the studies they have created and those they have joined. This central hub helps users keep track of their involvement and provides quick access to each study's data and settings.

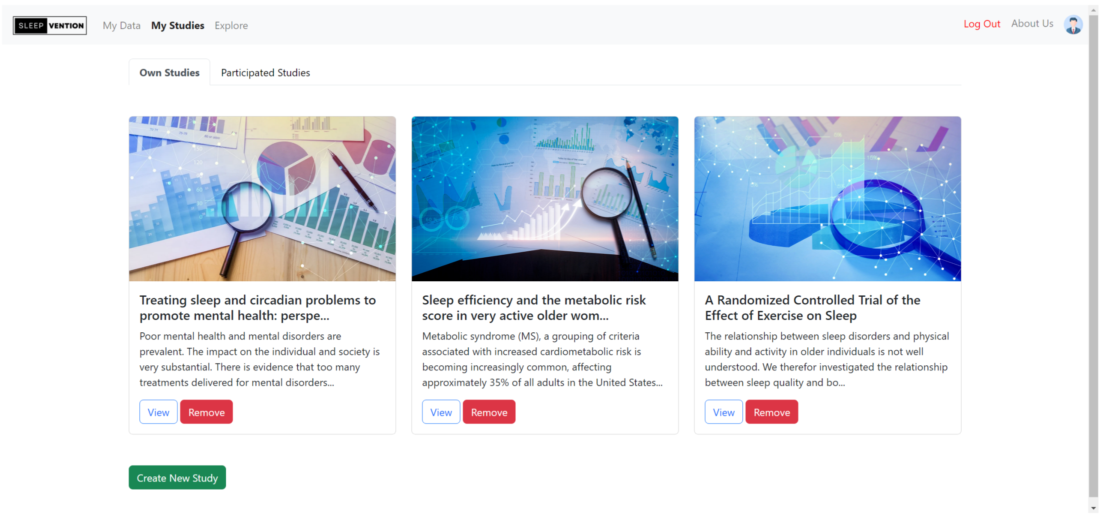

Figure 13. SleepVention studies page

Users can join studies through two primary methods. The first method involves browsing publicly available studies on the homepage and joining them directly by clicking the "Join Study" button. The second method is through invitations. When a researcher invites a participant to a private or public study, the user receives a message in their profile page with the option to review the study details and accept or decline the invitation.

Each study page displays its title, description, consent form link, and participant requirements. Depending on the user's role, the interface adapts accordingly. If the user is a participant, they see options to join or accept an invitation. If the user is the study creator, they have additional controls, such as editing the study, inviting other users, or downloading study data. Figure 14 shows a sample study page viewed as the study creator.

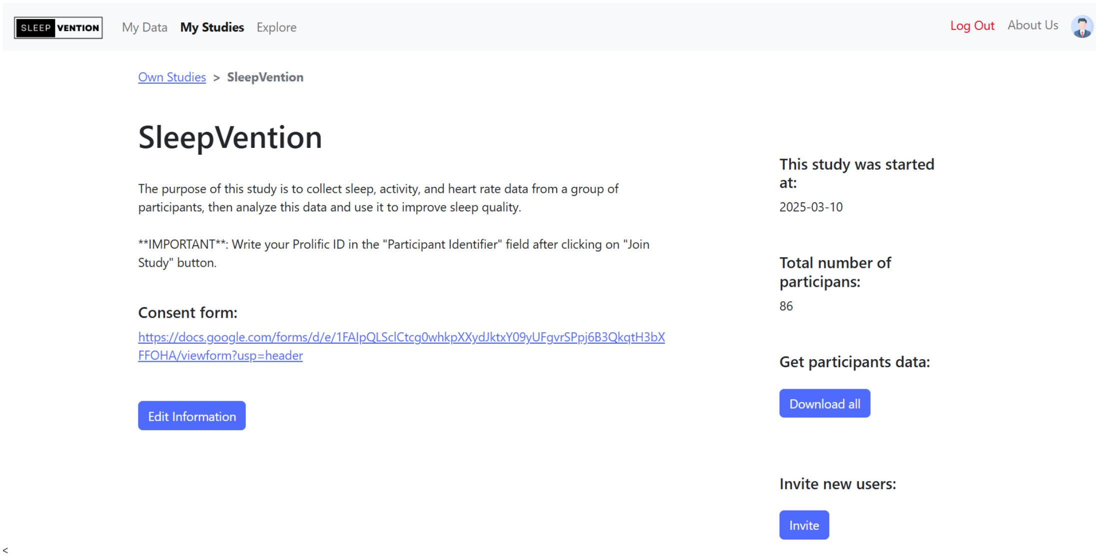

Figure 14. A study page accessed as the creator of the study

To create a new study, users navigate to the "Create New Study" page, shown in Figure 15. Here, they are prompted to enter the study name, a short description, the type of study (public or private), and a link to the consent form. An optional checkbox allows researchers to require participant identifiers, which can be useful for matching participants recruited via external platforms such as Prolific. Form validation is handled on the client side using JavaScript, including RegEx checks for the consent form URL.

For inviting participants, the study creator can use the invitation page, shown in Figure 16, where they enter the participant's username or email address. The system ensures the participant has not already been invited or enrolled. Once invited, the participant receives a message in their profile, where they can review the study details and decide whether to join.

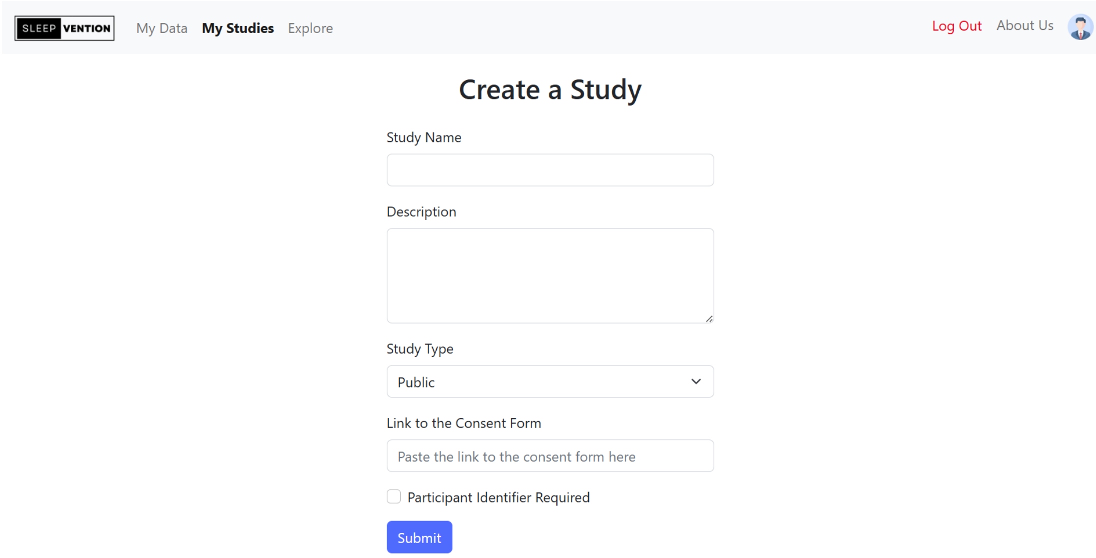

Figure 15. SleepVention create study page

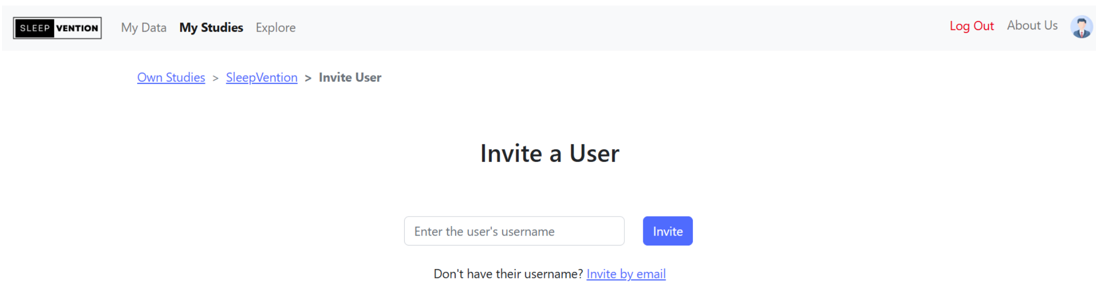

Figure 16. SleepVention study invitation page

4.1.6. User Data

Efficient management and visualization of user data are key features of SleepVention. The platform enables users to upload and review their own data collected through Fitbit APIs, as well as additional files uploaded manually. The "My Data" page serves as the main interface for viewing and managing this information.

To simplify the process of connecting Fitbit accounts, the platform follows a two-step OAuth authorization workflow. First, the user clicks the "Connect to Fitbit" button, prompting a dialog that explains what data will be accessed and how it will be used (Figure 18). Upon continuing, the user is redirected to Fitbit's authentication gateway.

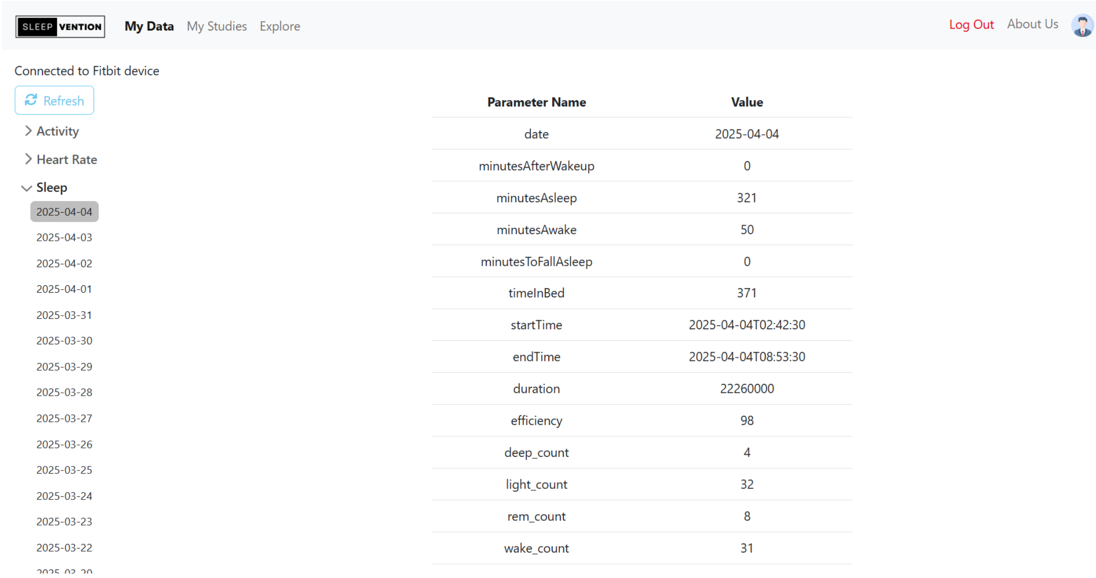

Figure 17. A sample of users' sleep data

After authorization, the platform securely stores the tokens required to fetch data from the Fitbit APIs.

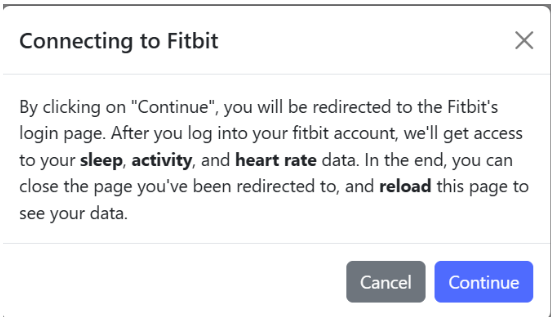

Figure 18. Dialog to confirm connecting to Fitbit and getting the user's data

Once connected, as shown in Figure 17, users can view their Fitbit data categorized into activity, heart rate, sleep, and sleep stages. For each category, the interface displays available dates, allowing users to navigate through their records easily. The data tables presented on the page reflect the exact structure and values retrieved from Fitbit, ensuring transparency and accuracy.

In addition to automated Fitbit data retrieval, users can manually upload files to the platform in case they experience issues with syncing or wish to contribute data from alternative sources. This is especially useful for accommodating studies that include data from devices or formats not supported via direct integration. The upload interface allows users to submit files with descriptions, which are then displayed and organized alongside Fitbit records. Figure 19 shows a sample uploaded file displayed on the data page.

SleepVention also provides interactive visualizations that help users gain insights into their sleep patterns. As Figure 20 outlines, charts display total sleep time, sleep stages (REM, deep, light, awake), and trends over weekly, monthly, and yearly intervals. The visualizations include average comparisons with all other users on the platform, enabling users to contextualize their data within a broader population.

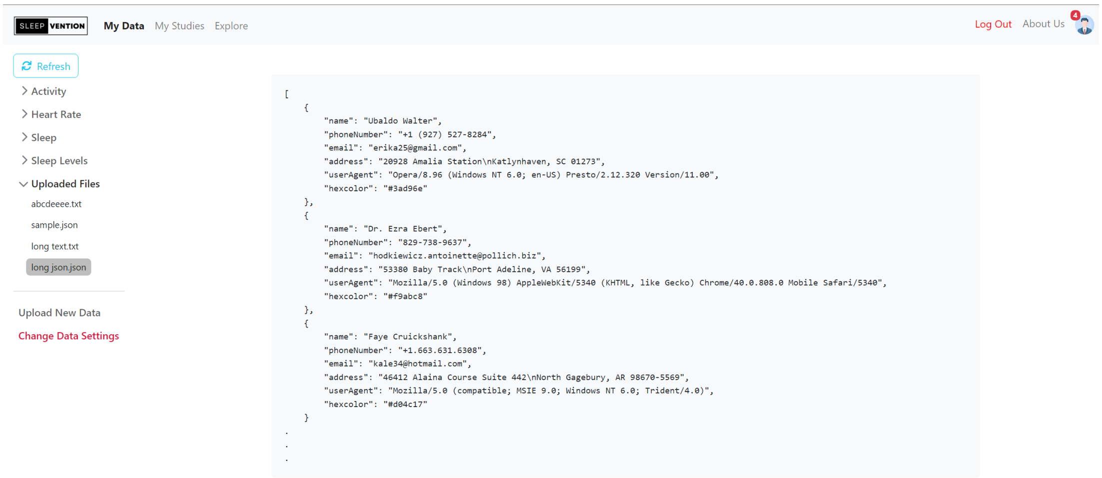

Figure 19. Showing a sample uploaded file in the data page

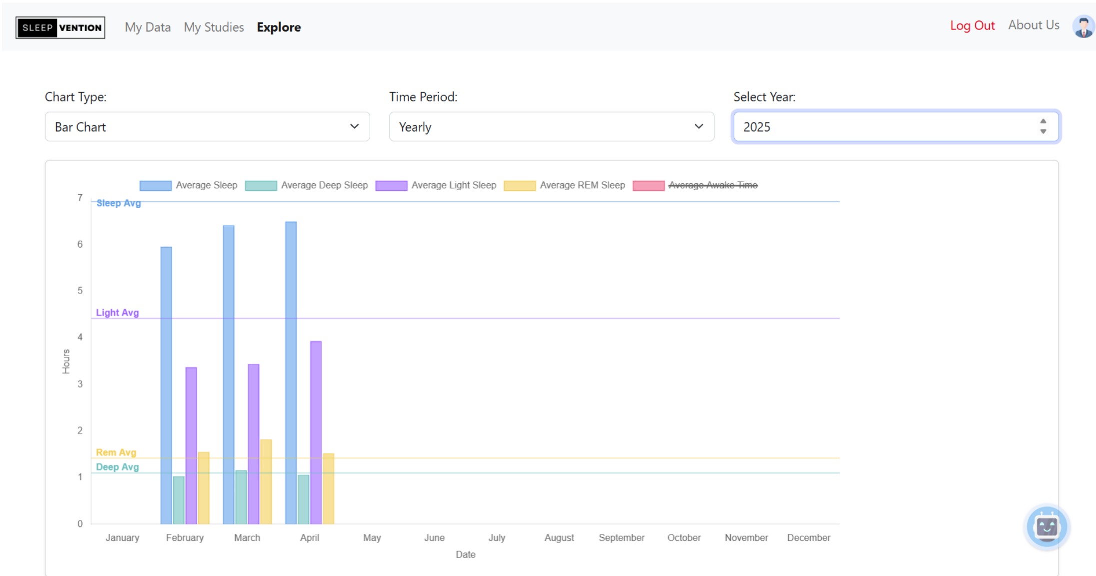

Figure 20. Sleep chart of a sample user showing yearly data of the user's average deep, REM, light, and overall sleep

4.2. Backend Server

This section provides an overview of the backend server application of the SleepVention platform. The backend server handles most of the platform's logical functionalities and data operations. To reduce UI complexity and increase security, no data is stored, changed, or processed on the user side, making the backend server responsible for all the data operations. The server validates the frontend requests and users' input data, handles internal errors, interacts with the database, and fetches data from the Fitbit APIs. The backend server is implemented by FastAPI and SQLite database. SQLAlchemy library is used as an Object Relational Mapper (ORM) to handle the interactions between the FastAPI application and the SQLite database. The following section explains the reasons behind these technology choices in detail.

4.2.1. Technology Choices

The backend server for the web application was developed using FastAPI, SQLite, and Pydantic and SQLAlchemy libraries. These technologies were selected based on their modern features, development efficiency, compatibility with research-oriented projects, and ability to deliver scalable and maintainable codebases.

FastAPI

FastAPI was chosen as the core web framework for building the RESTful API services. FastAPI is a modern, high-performance, asynchronous web framework for Python that emphasizes speed, data validation, and automatic API documentation generation [39]. Built on top of Starlette and Pydantic libraries, FastAPI enables developers to create clean, efficient, and robust APIs with minimal overhead. Its asynchronous support is particularly valuable for handling concurrent tasks, such as processing multiple client requests, without significant performance bottlenecks.

SQLite

SQLite was used as the database for data persistence. As a lightweight, serverless, and file-based database engine, SQLite is particularly well-suited for research and prototyping purposes [40]. It offers zero-configuration setup, fast read/write operations, and sufficient performance for the scale and complexity anticipated in this thesis project. Moreover, SQLite is embedded directly into the application, eliminating the need for a separate database server and simplifying deployment during the experimental phases.

Pydantic

Pydantic was used for data parsing and validation. Integrated tightly with FastAPI, Pydantic ensures that incoming and outgoing data conforms to predefined schemas with type safety guarantees. This automatic validation not only improves code robustness but also enhances security by minimizing the risk of processing malformed or malicious input [41].

SQLAlchemy

SQLAlchemy served as the Object-Relational Mapping (ORM) tool between the Python application and the SQLite database. By abstracting SQL operations into Pythonic models and queries, SQLAlchemy promotes cleaner, more maintainable, and database-agnostic code [42]. This choice also enables easy future transitions to more scalable database systems (e.g., PostgreSQL or MySQL) if needed, without requiring substantial rewriting of the database access layer.

4.2.2. APIs

The backend server of the web application provides a RESTful API built using FastAPI, enabling communication between the client interface and the database. The API endpoints were designed to support all interactions with the users and external services such as Fitbit APIs. The REST API consists of endpoints detailed in Table 1 used by the frontend application. Each endpoint initializes a new database session when called for the duration of the request, ensuring the statelessness of REST.

The API architecture emphasizes modularity, security, and scalability by separating responsibilities into four different layers:

- **Routing Layer**: Defines API endpoints using FastAPI decorators (e.g., `@app.post()`, `@app.get()`).
- **Schema Layer**: Utilizes Pydantic models to enforce strict data validation and serialization between requests and responses. Models are special Pydantic classes for validating data with Python types and more complex verifcation functions, for example in cases when an email should be verified with regex rules. Received and returned data in responses are automatically decoded or encoded from JSON, which is the main format in the REST APIs.
- **Database Access Layer**: Handles direct database interactions using SQLAlchemy ORM queries and abstractions in a separate CRUD module.
- **Error Handling Layer**: A custom universal exception handler ensures that validation errors, authentication errors, and unexpected exceptions are gracefully managed. In FastAPI, error codes that are raised as exceptions, are caught and turned into correct HTTP error codes to inform the requester about the error or incorrect request.

Each endpoint typically follows the pattern of:

1. **Authentication**: Except for a few API endpoints, such as getting public studies or login and register, all other actions require authentication in the server side. For authentication, access tokens that are passed via request headers are validated using utility functions. If the token is invalid, an unauthorized error response with 403 HTTP code will be returned.
2. **Request Validation**: Incoming data is parsed and validated using Pydantic schemas.
3. **Database Operation**: Operations such as user lookup, study creation, or Fitbit data updates are delegated to the CRUD module.
4. **Response Serialization**: Responses are serialized using Pydantic models to ensure all the responses returned from an API endpoint follow the same structure.

By implementing a clean separation of concerns, enforcing strict schema validation, and handling errors gracefully, the FastAPI program ensures a robust, secure, and maintainable server-side architecture for the SleepVention platform.

4.2.3. Database

The backend of the web application utilizes a structured relational database to store user information, Fitbit data, study details, and user-uploaded files. The database is managed using SQLite as the database engine, SQLAlchemy as the ORM tool, and is integrated with the server application through the FastAPI framework.

The database schema was designed with the following goals in mind:

- **Simplicity**: Making it easy and fast to develop to meet the thesis deadlines.
- **Data integrity**: Ensuring consistency between related data (e.g., users, studies, and Fitbit logs).
- **Extensibility**: Enabling easy future addition of new features or data types.
- **Efficiency**: Minimizing query complexity for real-time platform interactions.

Create, Read, Update, Delete (CRUD) operations are encapsulated in a separate module, ensuring a clean separation of concerns between API logic and data access logic. Furthermore, this approach leads to easier maintainability and testing of database operations, alongside with clear documentation of how each entity (user, study, Fitbit log) is manipulated.

4.3. Data Security and Privacy Measures

Ensuring the security and privacy of user data is a central focus of the SleepVention platform. Several measures have been implemented at different levels of the system architecture to protect sensitive information during storage, transmission, and processing.

Participant Anonymity

The SleepVention platform is designed to preserve the full anonymity of all research participants. When researchers download study data through the platform, the exported files include only a participant identifier and exclude all personal information such as names, email addresses, gender, or other demographic details.

The participant identifier is specified by the study creator during the study creation process. Participants are asked to provide this identifier when they join a study. This mechanism allows researchers to match data uploads with participant records without compromising personal privacy. It ensures that researchers can verify participant engagement while maintaining strict data anonymization.

In the case of the user study conducted in this thesis, the participant identifier was the Prolific ID assigned to each participant. This identifier was used to confirm study completion and to merge data across the SleepVention platform and the survey responses. At no point was personally identifiable information revealed to the researchers, aligning with best practices in ethical data handling and privacy-preserving research.

Secure data transmission

All communications between the client and server are conducted over the Hypertext Transfer Protocol Secure (HTTPS) protocol, ensuring that data transmitted over the network is encrypted and protected against interception, tampering, or eavesdropping. HTTPS secures login credentials, Fitbit tokens, and any personal or health-related data shared between users and the platform.

Authentication and access control

To maintain strict control over platform access, all pages and functionalities beyond general access pages (such as the public studies list and the about us page) require user authentication. Authentication is token-based, which means users are issued a secure session token upon login, which must be presented in request headers for accessing protected endpoints. Also, to prevent token hijacking or misuse, tokens are automatically expired and invalidated after one day.

Password protection

User passwords are never stored in plaintext. Instead, all passwords are salted and hashed using the bcrypt hashing algorithm before being stored in the database, ensuring that even if database access were compromised, the original passwords remain secure. During registration, users must create passwords that meet minimum security criteria: passwords must be at least eight characters long and include a combination of uppercase letters, lowercase letters, and numbers. This reduces the risk of brute-force and dictionary attacks.

Fitbit security measures

The platform integrates with Fitbit APIs to collect sleep and activity data. The security of this data collection process is guaranteed by Fitbit itself, which enforces the recommended PKCE and OAuth 2.0 protocol. This removes the need to store the client's secret value in the code but rather uses unique values for state, code verifer, and code challenge for each authorization request. The code verifer is a cryptographically random value of length between 42 and 128 characters, the code challenge is a base64-URL encoded SHA-256 hashed version of the code verifer and the state is a unique value created in the application and passed along the query parameters of the authorisation URL and then sent back as part of the response

These combined measures ensure that user privacy is respected, sensitive information is protected throughout its lifecycle, and data handling complies with fundamental standards of secure system design.

5. STUDY DESIGN

To answer the research questions defined in Section 1.2, two user studies were conducted; One to gather users' feedback about the usefulness and importance of the SleepVention platform and one to research the relationship between smartphone addiction and sleep quality. Two separate questionnaires were designed for the two user studies, and both of them were going to be answered consequentially by the participants at the end of the study. Before beginning the main study, a small-scale pilot study was conducted with 10 participants to test the study instructions and identify potential issues of the SleepVention platform that could cause the system to crash or behave unexpectedly.

5.1. Study Procedure

Initially, this study was considered to have around 100 participants, having that in mind that some of them will fail to complete the study due to technical or non-technical issues. Later on, this number changed to 93 participants, that 31 of them completed the study successfully, which was enough data for the scope of this study. The study was carried out on Prolific, and all the recruited participants were required to have the following criteria:

- Own a desktop device.
- Own an activity tracker excluding smart watches (e.g. Fitbit, Xiaomi Mi Band, Microsoft Band).
- Be fluent in English.

Also, in the description and instructions of the study, it was emphasised that every participant needs to have access to a Fitbit device with sleep-tracking capabilities and have used it at least 20 days in the past 2 months.

At the beginning of the study, the participants were given a link to the instructions document. In the instructions document, participants were guided how to create an account in SleepVention, connect their Fitbit devices, fill out the consent form, join the study in the platform and share their data. After finishing all the tasks, the participants were asked to answer 2 questionnaires, one for smartphone addiction and the other one to get their opinion about the SleepVention platform and the idea behind it. The participants' Prolific Identity Document (ID) were asked in both questionnaires and in the platform when joining the study; These IDs were used to check if the participants have filled out the questionnaires and uploaded their data successfully to the platform. Prolific IDs were also used later to merge the data from different sources for analysis purposes.

5.2. Questionnaires

This section describes the two questionnaires that were used in this study. Each questionnaire was designed to answer one of the research questions mentioned in

Section 1.2. All questionnaires in this study were implemented and answered on Google Forms.

5.2.1. Sleep Research Platform Questionnaire

This questionnaire consists of 9 questions, and is designed to answer RQ1. The questionnaire is designed to get participants opinion about the importance of sleep quality, a platform for sleep research, and their willingness to share their data for sleep research. One of the questions is a Yes/No question and the other eight are five-point Likert scale. The questions and their answer choices are mentioned in the following.

- **Q1: How important is sleep quality to you?**
  - 1: Not important at all
  - 2: Very important
- **Q2: Do you currently use any devices or apps to monitor your sleep?**
  - Yes
  - No
- **Q3: In your opinion, how useful can be an online platform designed specifically for sleep research?**
  - 1: Not useful at all
  - 5: Very useful
- **Q4: How much do you think a sleep research platform can help researchers to collect data more conveniently?**
  - 1: Not at all
  - 5: Very mcuh
- **Q5: How much do you think a sleep research platform can encourage researchers to conduct more sleep-related studies?**
  - 1: Not at all
  - 5: Very much
- **Q6: How much do you think a sleep research platform can encourage normal people to engage more in sleep studies and share their data for this purpose?**
  - 1: Not at all
  - 5: Very much
- **Q7: How willing are you to share your data for sleep research for a fee?**
  - 1: Not willing at all

  - 5: Very willing

- **Q8: How willing are you to share your data for sleep research for free?**
  - 1: Not willing at all
  - 5: Very willing

- **Q9: How willing are you to share your data for your own benefit?**
  - 1: Not willing at all
  - 5: Very willing

5.2.2. Smartphone Addiction Questionnaire

After completing the first questionnaire, participants are asked to answer the second questionnaire for smartphone addiction. Two methods are included in this questionnaire to assess smartphone addiction: SPAI and SAS-SV.

The SPAI consists of 26 questions designed to evaluate various dimensions of problematic smartphone behavior, including compulsive use, withdrawal symptoms, and interference with daily activities. Each item is rated on a 4-point Likert scale, ranging from 1 (strongly disagree) to 4 (strongly agree). A participant is classified as addicted if they rate at least 13 of the 26 items—a threshold corresponding to half or more of the items—with a score of 3 or 4. This scoring criterion reflects the presence of multiple behavioral indicators associated with smartphone dependency.

The SAS-SV is a 10-item screening tool developed to provide a brief yet reliable assessment of smartphone addiction risk. Responses are given on a 6-point Likert scale, from 1 (strongly disagree) to 6 (strongly agree), with higher total scores indicating greater addiction severity. In accordance with previous studies, a cumulative score of 29 or higher was used in this study as the cutoff for classifying participants as addicted. The SAS-SV captures behavioral patterns such as preoccupation with the smartphone, withdrawal, tolerance, and daily life disturbance.

It was decided to incorporate both the SPAI and SAS-SV classification methods for this study, to ensure the robustness of smartphone addiction findings in relation to sleep behavior.

5.3. Data Analysis Approach

The first step in data analysis was cleaning the datasets. As mentioned in Section 6.1, From the 93 individuals who participated in this study, only 31 completed all the required steps. Therefore, it was necessary to remove the data of participants who did not finish the study, before doing the data analysis. Also, in order to compare the sleep data and smartphone addiction, the data of 2 separate sources needed to merge into one single dataset. Data pre-processing, including data cleaning and merging separate datasets, were done by Python.

The next step in data analysis was creating meaningful data and charts from the raw datasets. In this step, Google Sheets and its built-in functions were used the most to calculate aggregated data like sum and average, and to create related data visualizations. Also, ChatGPT was used during the data analysis process to explain the data for better understanding and to create tables in LaTeX format.

6. RESULTS

6.1. Participant Demographics

The data collection for SleepVention project was done in 3 steps. The study was first opened in Prolifc on the 27th of March, 2025, with 10 participants as a test step for the main data collection. The main requirement of the study was to have a Fitbit device and proficiency in English. From the 10 participants, only 1 was able to finish the study successfully and complete all the required tasks. The main problem of the most participants was not being able to upload their Fitbit data on the SleepVention platform. The either didn't have a Fitbit device, or haven't used it in the last 2 months.

After this poor outcome, based on the data gathered from the previous step and the participants' feedback, we changed the experiment guidelines and corrected the confusing parts and the sections with the most incorrect or incomplete data. Also, we added a new criteria of having 90% approval rate from the previous participated studies. After these modifications, the second round of the data collection experiment was held in Prolific on the 15th of April, 2025, with 31 participants. This time, 8 participants out of 31, managed to finish the study and complete all tasks, which was a great improvement.

The 3rd round of the data collection experiment was carried out in Prolific on the 16th of April, 2025, with minor changes on the guidelines and setting the participants' study approval rate to 90%. This time from 52 participants, 22 of them completed the study successfully. In the end, we managed to gather data of 31 participants in total.

As shown in Table 2, the sample was diverse in terms of age, gender, and employment status. The participants had a mean age of 37.7 years (SD = 13.5), reflecting a diverse adult sample. The gender distribution was balanced, with 51.9% identifying as female and 48.1% as male. In terms of educational engagement, 19.2% of participants were students, while 71.2% reported not being students at the time of the study. Employment status varied, with the majority employed full-time (65.4%), followed by part-time employment (19.2%) and others, including retired, unemployed, or non-working (15.4%).

Ethnically, the sample was predominantly White (61.5%), with representation from Black (30.8%) and Asian (7.7%) communities. The majority of participants resided in English-speaking countries, including the United Kingdom (32.7%), South Africa (23.1%), and the United States (17.3%), with smaller proportions from Canada and Indonesia.

Table 2. Summary of Participant Demographics

Variable	**Value(s)**
Total Participants	31
Average Age (SD)	37.7 (13.5)
Sex	51.9% Female, 48.1% Male
Student Status	19.2% Yes, 71.2% No
Employment Status	65.4% Full-Time, 19.2% Part-Time, Others
Ethnicity	61.5% White, 30.8% Black, 7.7% Asian
Top Countries of Residence	UK, South Africa, US, Canada, Indonesia

6.2. Usefulness of the Platform

As described in Section 5.2.1, a questionnaire was designed to get the participants' feedback regarding SleepVention's usefulness and its importance. The purpose of the questionnaire was to see how many of the participants already use an external platform or application for tracking and improving their sleep quality, how much they think this concept is important, and how much SleepVention has succeeded in achieving its goals as a platform to help improving sleep quality. The following sections describe different insights of the study results in detail.

6.2.1. Perceived Importance of Sleep Quality

As the first question, participants were asked to rate the importance of sleep quality on a 5-point Likert scale, where 1 represented "Not important at all" and 5 represented "Very important." A total of 20 participants responded to this item. The responses demonstrated a strong consensus toward valuing sleep quality, with a mean rating of 4.65 (SD = 0.67).

As shown in Figure 21, the majority of participants selected ratings of 4 or 5, with 75% rating sleep quality as "Very important." Only a small minority selected neutral or moderately important responses, and no participant rated sleep quality below 3. These results suggest that the participant population is generally highly conscious of the role that sleep plays in their well-being, supporting the relevance and potential engagement with sleep-related technologies and studies.

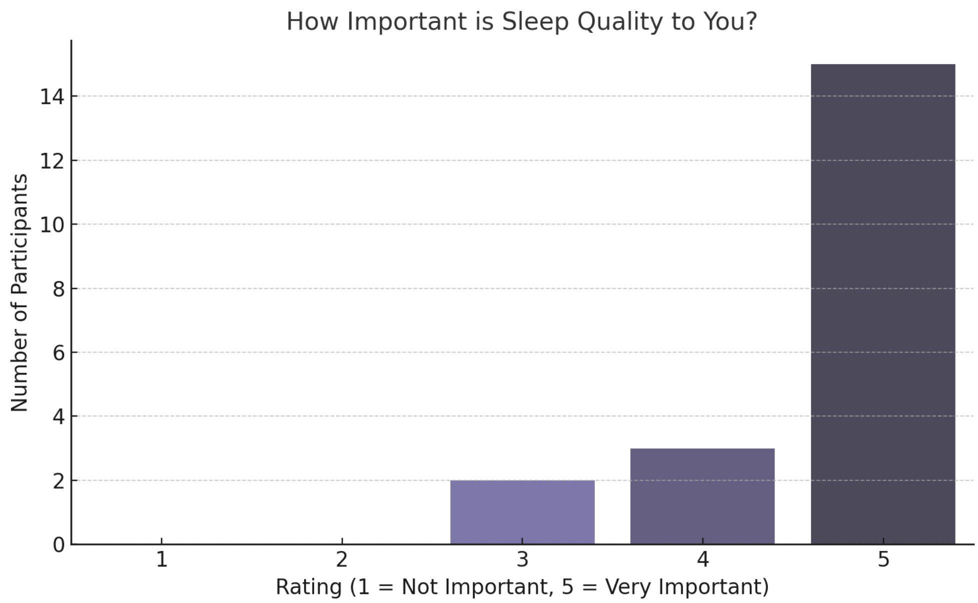

Figure 21. Participant Responses to Sleep Importance Question

6.2.2. Use of Sleep Monitoring Technologies

To complement the question on perceived sleep importance, participants were also asked whether they currently use any devices or applications to monitor their sleep patterns. As Figure 22 indicates, a substantial majority, 90% of respondents, reported using sleep-tracking technologies, while only 10% indicated they did not.

This high rate of adoption suggests a strong alignment between participants' stated valuation of sleep quality and their behavioral engagement with tools that support sleep awareness. The results reinforce the idea that participants not only recognize the importance of sleep but are also proactive in leveraging technology to monitor and potentially improve their sleep habits.

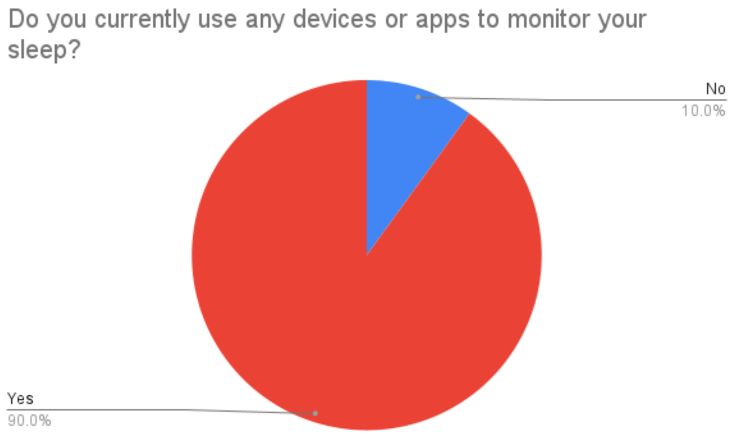

Figure 22. Usage of Sleep Monitoring Devices or Applications between the Participants

6.2.3. Perceived Value of a Sleep Research Platform

Furthermore, participants were asked to evaluate the potential value of an online platform specifically designed for sleep research. This set of questions aimed to assess the perceived usefulness of such a platform in supporting researchers and promoting participant engagement. Responses were recorded on a 5-point Likert scale, with higher values indicating stronger agreement or perceived usefulness.

As Figure 23 suggests, most participants demonstrated a highly positive outlook regarding the role of sleep research platforms. On average, the perceived usefulness of such platforms (Q3: In your opinion, how useful can be an online platform designed specifically for sleep research?) was rated at 4.30. And the potential for facilitating data collection (Q4: How much do you think a sleep research platform can help researchers to collect data more conveniently?) was rated even higher, at 4.65. Participants also rated the likelihood of such platforms encouraging researchers to conduct more studies (Q5: How much do you think a sleep research platform can encourage researchers to conduct more sleep-related studies?) at 4.50. And rated the ability to motivate individuals to engage in sleep studies (Q6: How much do you think a sleep research platform can encourage normal people to engage more in sleep studies and share their data for this purpose?) at 4.35.

These results indicate that participants generally believe in the scientific and social potential of centralized digital platforms for sleep research. The consistent clustering of responses around values 4 and 5 across all four items suggests a strong consensus in support of the idea. Most notably, thirteen participants rated the data collection benefits at the highest level (5), and eleven participants similarly rated the platform's ability to motivate further research at the highest level.

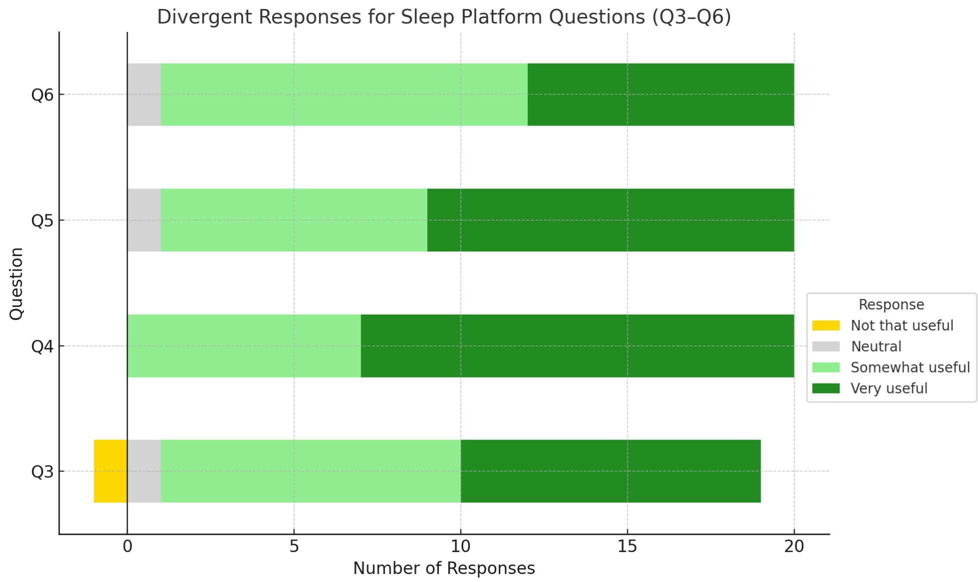

Figure 23. Average Ratings for Sleep Research Platform Usefulness Based on the Participant Responses to Questions 3 to 6 Mentioned in Section 5.2.1

6.2.4. Willingness to Share Personal Sleep Data

In the end, participants were asked to indicate their willingness to share sleep data under three distinct conditions: for a fee (Q7), for free (Q8), and for their own benefit (Q9). Responses were recorded on a 5-point Likert scale, where higher values indicated greater willingness.

The results reveal notable differences in willingness across conditions. Participants showed the highest average willingness to share their data for a fee, with a mean score of 4.50. This was followed by willingness to share for their own benefit (mean = 4.15). In contrast, the willingness to share data for free was substantially lower, with a mean score of only 2.89.

As shown in Figure 24, more than half of the participants gave the highest possible rating (5) when asked about sharing data for compensation. For data sharing motivated by personal benefit, responses also clustered in the upper range, with nine participants giving a rating of 5 and seven selecting 4. On the other hand, willingness to share for free was more evenly distributed across the response scale. Notably, a third of participants selected low willingness values (1 or 2), indicating some reluctance to share personal data without incentive or personal gain.

These results suggest that participants perceive their sleep data as valuable and are more likely to engage in data sharing when offered compensation or tangible personal benefits. The findings have implications for the design of data-driven health research platforms, which may need to incorporate benefit-driven or incentive-based models to encourage sustained participation.

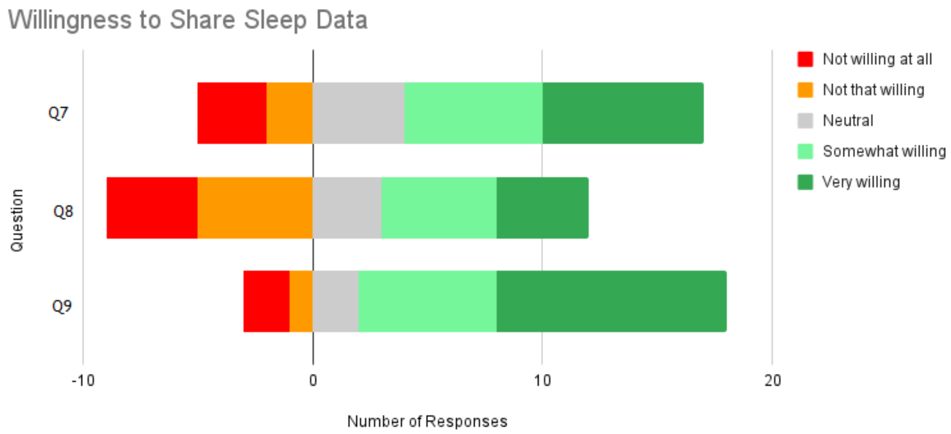

Figure 24. Average Ratings for Willingness to Share Sleep Data Based on the Participant Responses to Questions 7 to 9 Mentioned in Section 5.2.1

6.3. Relationship Between Smartphone Addiction and Sleep Quality

In the next part, to examine how smartphone addiction may influence sleep quality, a study was carried out on the SleepVention platform to find the relationship between sleep data collected through Fitbit devices and standardized self-report addiction questionnaires. Two primary sleep-related metrics were used from Fitbit APIs: sleep duration and sleep efficiency. Sleep duration represents the total time a participant spent asleep during each night, measured in minutes. Sleep efficiency reflects the proportion of time spent asleep relative to the total time spent in bed, expressed as a percentage. This metric accounts not only for sleep quantity but also for how efficiently participants transitioned to and remained in a sleep state.

Smartphone addiction was assessed using two validated instruments: the Smartphone Problematic Use Scale (SPAI) and the Smartphone Addiction Scale – Short Version (SAS-SV). The SPAI consists of 26 items rated on a 4-point Likert scale. A participant is classified as addicted if they rate at least 13 of the 26 items (i.e., half or more) with a score of 3 or 4, indicating problematic use. In contrast, the SAS-SV comprises 10 items scored on a scale from 1 to 6. Participants with a cumulative score of 29 or higher are categorized as addicted according to this measure.

The following subsections compare sleep duration and sleep efficiency across addicted and non-addicted groups as defined by each scale, to assess whether excessive smartphone use is associated with diminished sleep quality.

6.3.1. Relationship Between Smartphone Addiction and Sleep Duration

To explore whether smartphone addiction influences sleep behavior, participants' average nightly sleep duration was compared across two independent addiction classifications: SPAI (Smartphone Problematic Use Scale) and SAS-SV (Smartphone Addiction Scale – Short Version). Participants were categorized as "Addicted" or "Not addicted" based on each respective scale, and their average sleep duration was calculated from Fitbit-derived metrics.

As pictured in Figure 25, the results revealed only minor differences in sleep duration between addicted and non-addicted groups. Participants classified as addicted under the SPAI criteria had an average sleep duration of 6.39 hours, while those not addicted averaged 6.78 hours. Similarly, under the SAS-SV classification, addicted individuals reported 6.50 hours of sleep compared to 6.84 hours for non-addicted participants.

To statistically assess these differences, independent two-sample t-tests were conducted. For the SPAI classification, the t-test yielded a statistic of -0.705 with a p-value of 0.500, indicating no statistically significant difference in sleep duration. For the SAS-SV classification, the t-value was -0.906 with a p-value of 0.374. These results confirm that sleep duration was not significantly different between smartphone addicted and non-addicted participants in this study.

These differences, though directionally consistent with the hypothesis that smartphone overuse may lead to reduced sleep, are small and unlikely to be of practical or statistical significance. The overlap in average sleep duration across addiction groups suggests that smartphone addiction, as measured in this study, does not have a clear or substantial impact on nightly sleep quantity.

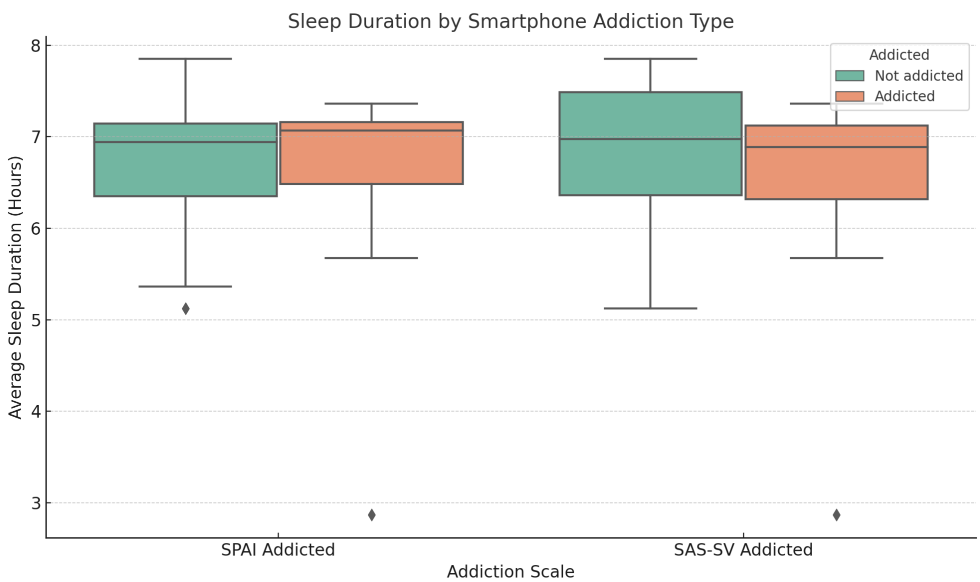

Figure 25. Comparing Sleep Duration Between Participants with and without Smartphone Addiction Based on SPAI and SAS-SV classifications

6.3.2. Relationship Between Smartphone Addiction and Sleep Start Time

In addition to analyzing sleep duration, this study examined whether smartphone addiction influences the time at which participants typically begin their nightly sleep. Using timestamped data retrieved from Fitbit APIs, the average sleep onset time for each participant was calculated. To better capture late-night behavior, the sleep start hour was shifted such that the 24-hour clock begins at noon (12:00) and ends at 11:59 the following day. This transformation ensures that sleep onset during late-night hours is visually and statistically centered within the analysis window.

Figure 26 shows a box plot comparing average sleep start times between addicted and non-addicted participants, divided by the SPAI and SAS-SV classifications, revealing a slight visual trend: non-addicted individuals tended to fall asleep marginally earlier than those classified as addicted. However, the observed differences were small and not statistically significant. Independent samples t-tests confirmed that the differences in sleep start time between addiction groups were not significant for either the SPAI (t = 0.68, p = 0.51) or SAS-SV (t = 0.90, p = 0.38) classifications. These findings suggest that while there may be a modest tendency for addicted individuals to go to sleep later, the evidence is insufficient to support a reliable effect of smartphone addiction on sleep onset time.

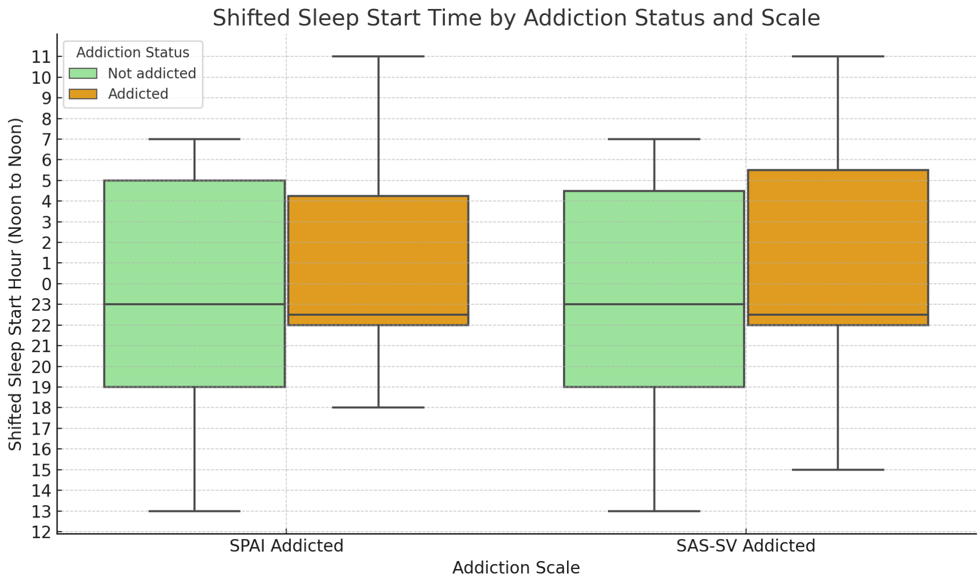

Figure 26. Comparing Sleep start time Between Participants with and without Smartphone Addiction Based on SPAI and SAS-SV classifications

6.3.3. Relationship Between Smartphone Addiction and Sleep Efficiency

To assess the potential impact of smartphone addiction on sleep quality, sleep efficiency was analyzed across participants categorized as addicted or not addicted based on two validated scales: the Smartphone Problematic Use Scale (SPAI) and the Smartphone Addiction Scale – Short Version (SAS-SV).

As demonstrated in Figure 27, participants classified as addicted under the SPAI scale had an average sleep efficiency of 94.29 percent, compared to 89.14 percent for those not classified as addicted. Similarly, the average sleep efficiency among SAS-SV addicted individuals was 93.72 percent, while the non-addicted group exhibited a slightly lower mean of 87.50 percent.

Independent t-tests were used to evaluate whether these differences were statistically significant. For the SPAI classification, the t-value was 1.935 with a p-value of 0.067, while for the SAS-SV classification, the t-value was 1.681 with a p-value of 0.116. Although these values suggest a trend toward higher efficiency among addicted participants, the differences did not reach statistical significance at the conventional 0.05 threshold.

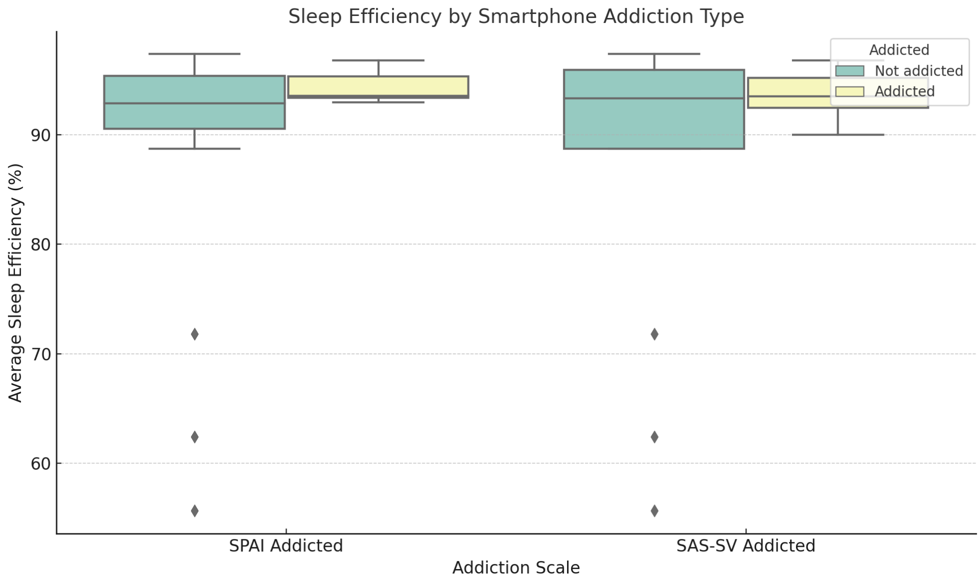

Figure 27. Comparing Sleep Efficiency Between Participants with and without Smartphone Addiction Based on SPAI and SAS-SV classifications

Despite these differences in mean values, the results do not suggest a consistent or interpretable trend that would support the hypothesis that smartphone addiction reduces sleep quality. In fact, addicted participants showed numerically higher efficiency scores in both classifications. This counterintuitive outcome may stem from variability in sleep behavior not captured by the efficiency metric alone, such as bedtime irregularity or total sleep duration.

7. DISCUSSION

7.1. Findings

This thesis sought to answer two primary research questions, as outlined in Section 1.2. These questions guided both the development of the SleepVention platform and the subsequent empirical investigation conducted using the platform. Below, the findings related to each research question are discussed in detail, placing them within the context of existing literature and highlighting their implications for future research and practical applications.

7.1.1. RQ1: How Useful and Important Is an Online Platform for Sleep Research?

The investigation into the usefulness and importance of an online platform specifically designed for sleep research revealed highly positive feedback from the participants. Users reported substantial benefits regarding the convenience and effectiveness of SleepVention for collecting and managing sleep data. The questionnaire results, detailed in Section 6.2, indicated strong support for the platform, particularly highlighting its capability to facilitate easier data collection, encourage researchers to conduct further studies, and motivate participants to actively engage in sleep-related research. These findings align with previous research that underscores the value of digital platforms in enhancing the efficiency of data collection and participant recruitment in research contexts.

Participants exhibited considerable willingness to share their sleep data under specific conditions. Data sharing was significantly more favored when participants anticipated receiving compensation or direct personal benefit, compared to sharing data freely. This finding supports the assertion in existing literature regarding the importance of incentivizing data sharing to sustain user engagement in digital health platforms. Overall, SleepVention has demonstrated significant potential to address common challenges in sleep research, such as participant recruitment and efficient data handling, thus contributing positively to the advancement of sleep science.

7.1.2. RQ2: Can Smartphone Addiction Cause Poor Sleep Quality? If So, How Much Can It Affect Sleep Quality?

The second research question aimed to examine the relationship between smartphone addiction and sleep quality. Data collected from Fitbit devices combined with results from the Smartphone Addiction Inventory (SPAI) and Smartphone Addiction Scale - Short Version (SAS-SV) questionnaires provided an opportunity for empirical examination of this relationship.

Interestingly, the results indicated only minor differences in sleep duration, start time, and efficiency between participants classified as addicted and those not classified as addicted according to both SPAI and SAS-SV measures. Contrary to expectations based on previous literature, smartphone addiction in this study was not significantly correlated with reduced sleep duration, later sleep time, or poorer sleep efficiency. In fact, sleep efficiency was slightly higher among participants categorized as addicted, which was an unexpected outcome.

These findings suggest a more nuanced relationship between smartphone usage and sleep quality than commonly reported in existing literature. It may imply the presence of compensatory behaviors or other mediating factors not captured directly by sleep duration, start time, and efficiency metrics alone. The results highlight the necessity of considering additional variables, such as bedtime routines, screen exposure timing, and specific smartphone usage patterns, to better understand the complexities of how smartphone addiction might influence sleep quality.

Given the limited evidence found for a substantial negative impact of smartphone addiction on sleep within the parameters of this study, future research should explore broader behavioral and contextual factors. More comprehensive measures of smartphone usage, as well as longitudinal approaches, might yield clearer insights into potential causal mechanisms and allow for more targeted interventions.

In summary, while the present study did not strongly support the hypothesis that smartphone addiction directly impairs sleep quality, it underscores the need for continued investigation using more detailed behavioral data and extended research designs.

7.2. Limitations

To gain enough data, the study was originally planned to be conducted with roughly 100 participants. In the end, the amount of participants completing all sections of the study was significantly smaller than what was expected. Connecting to the Fitbit device in the platform was probably the reason for most of the failed submissions. The Prolific platform that hosted the study does not provide any means to filter the participants by owning a Fitbit device. And regardless of emphasizing this constraint in both the study description and instructions, it was obvious that many participants did not read the instructions thoroughly and therefore, some of them were not able to upload their Fitbit data to the platform.

Furthermore, Fitbit APIs have limitations on the number of records given in a single query and the number of queries per hour. For most APIs, the maximum data given in a single request was 100 records or data in a range of 30 days. Also, more than 150 requests per hour to the Fitbit APIs were not allowed. These constraints prevented us from getting the whole data of each participant and we decided only to get the data of the last 60 days for each participant. These limitations naturally resulted in a smaller quantity of and less distributed data, which may have impacted the reliability of the results.

7.3. Future Work

This thesis has established a foundational platform for sleep research, highlighting substantial potential to streamline data collection and enhance user engagement. However, several opportunities for future development remain, which could substantially broaden the applicability, functionality, and user experience of the

SleepVention platform. Expanding the platform's capability to integrate data from a wider range of popular sleep-tracking devices, such as Oura Ring, Dreem headband, and Apple Watch, would significantly enhance its utility. Integration of multiple devices would accommodate a larger and more diverse participant base, enabling comprehensive comparative studies across different device modalities and increasing the robustness of collected data.

While basic data visualizations are currently provided for sleep data, more sophisticated, interactive, and detailed graphical representations could be implemented. Future enhancements could include the data of user activities, heartrate, sleep stages, and other sleep-related data to enable users and researchers to gain deeper insights into sleep patterns and behaviors.

Introducing a feature allowing users to anonymously view and compare their data with other users could also be significantly valuable. This functionality could enable users to compare their data with other users' with similar characteristics and research what actions can lead them to better sleep quality. Implementation of strict privacy safeguards and anonymization techniques would be essential to ensure user trust and compliance with data protection regulations.

The current platform is only able to collect the users' data of the last 60 days. Extending the current capability to retrieve the whole history of users' data would offer more robust longitudinal insights into sleep patterns and trends. Such extended data access could facilitate richer research opportunities, enabling longitudinal studies to examine the effects of interventions and lifestyle changes on sleep quality over extended periods.

Lastly, incorporating an AI-driven chatbot feature would enable users to engage interactively with their sleep data. A Large Language Model (LLM) chatbot could answer user queries about different aspects of their data, offer personalized sleep improvement recommendations, and maybe provide educational information. This AI-driven interaction could greatly enhance user engagement by preventing users from relying solely on data tables and charts. By addressing these areas of future work, SleepVention could significantly advance its scope, usability, and impact, solidifying its position as a leading digital platform for sleep research and user engagement.

8. SUMMARY

This thesis presented the design, implementation, and evaluation of SleepVention, an online platform developed to facilitate sleep research through automatic data collection, study management, and user engagement. Recognizing the growing significance of sleep quality for public health and the challenges associated with conducting large-scale sleep studies, this work proposed a comprehensive digital solution to support both researchers and participants.

The platform was implemented using modern web technologies, including FastAPI for backend services and a JavaScript-based frontend interface. Integration with Fitbit APIs enabled the automatic collection of sleep-related data, while a flexible study management system allowed users to create, join, and monitor participation in both public and private research studies. The user interface was designed with simplicity and usability in mind, supporting secure authentication, intuitive navigation, and personalized dashboards.

In addition to system development, the platform was evaluated through two user studies. The first assessed the perceived usefulness and importance of a specialized sleep research platform. Results indicated that participants valued the ability to contribute to sleep research and showed a high willingness to share their data, especially when motivated by personal benefit or compensation. The second study explored the potential relationship between smartphone addiction and sleep quality, using standardized self-report questionnaires (SPAI and SAS-SV) and objective sleep metrics collected via Fitbit. Although minor differences were observed, no strong correlation was found, suggesting the need for further investigation with more detailed data.

Overall, this work demonstrated the feasibility and impact of combining wearable technology, user-centered design, and research infrastructure into a unified platform. SleepVention lays the groundwork for future development in participatory sleep science and opens the door to broader applications in health research. Recommendations for future enhancements include expanding device compatibility, improving visual analytics, enabling anonymous data comparisons, and incorporating intelligent support agents to enhance user experience and insight.

By bridging the gap between sleep researchers and everyday users, SleepVention offers a novel contribution to digital health platforms and reinforces the potential of technology-assisted research in understanding and improving human well-being.

9. REFERENCES

[1] Brink-Kjaer A., Leary E.B., Sun H., Westover M.B., Stone K.L., Peppard P.E., Lane N.E., Cawthon P.M., Redline S., Jennum P., Sorensen H.B.D. & Mignot E. (2022) Age estimation from sleep studies using deep learning predicts life expectancy. NPJ Digital Medicine 5, p. 103.

[2] Lee S., Mu C.X., Wallace M.L., Andel R., Almeida D.M., Buxton O.M. & Patel S.R. (2022) Sleep health composites are associated with the risk of heart disease across sex and race. Scientific Reports 12, p. 2023.

[3] Prather A.A. (2019) Sleep, stress, and immunity. In: M.A. Grandner (ed.) Sleep and Health, Academic Press, Cambridge, 1 ed., pp. 319–330.

[4] Scott A.J., Webb T.L., Martyn-St James M., Rowse G. & Weich S. (2021) Improving sleep quality leads to better mental health: a meta-analysis of randomised controlled trials. Sleep Medicine Reviews 60, p. 101556. URL: https://linkinghub.elsevier.com/retrieve/pii/S1087-0792(21)00141-6.

[5] Buysse D.J., Reynolds C.F., Monk T.H., Berman S.R. & Kupfer D.J. (1989) The pittsburgh sleep quality index (psqi): A new instrument for psychiatric research and practice. Psychiatry Research 28, pp. 193–213.

[6] Newington L. & Metcalfe A. (2014) Factors influencing recruitment to research: qualitative study of the experiences and perceptions of research teams. BMC Medical Research Methodology 14, p. 10. URL: https://bmcmedresmethodol.biomedcentral.com/articles/10.1186/1471-2288-14-10.

[7] Mukherjee S., Patel S.R., Kales S.N., Ayas N.T., Strohl K.P., Gozal D. & Malhotra A. (2015) An official american thoracic society statement: the importance of healthy sleep. recommendations and future priorities. American journal of respiratory and critical care medicine 191, pp. 1450–1458.

[8] Altevogt B.M. & Colten H.R. (2006) Sleep disorders and sleep deprivation: An unmet public health problem. National Academies Press.

[9] Ohlmann K.K., O'Sullivan M.I., Berryman P. & Lukes E. (2009) The costs of short sleep. AAOHN Journal 57, pp. 381–387.

[10] Perry G.S., Patil S.P. & Presley-Cantrell L.R. (2013) Raising awareness of sleep as a healthy behavior. Preventing chronic disease 10.

[11] Althoff T., Horvitz E., White R.W. & Zeitzer J. (2017) Harnessing the web for population-scale physiological sensing: A case study of sleep and performance. In: Proceedings of the 26th International Conference on World Wide Web, International World Wide Web Conferences Steering Committee, pp. 113–122.

[12] (2023), Fitbit device prices in gigantti electronics store. URL: https://www.gigantti.fi/search/fitbit, accessed: 25-05-2025.

[13] Menghini L., Yuksel D., Goldstone A., Baker F.C. & de Zambotti M. (2021) Performance of fitbit charge 3 against polysomnography in measuring sleep in adolescent boys and girls. Chronobiology International 38, pp. 1010–1022.

[14] Haghayegh S., Khoshnevis S., Smolensky M.H., Diller K.R. & Castriotta R.J. (2019) Accuracy of wristband fitbit models in assessing sleep: systematic review and meta-analysis. Journal of Medical Internet Research 21, p. e16273.

[15] Liang Z. & Chapa-Martell M.A. (2019) Accuracy of fitbit wristbands in measuring sleep stage transitions and the effect of user-specific factors. JMIR mHealth and uHealth 7, p. e13384.

[16] Kuosmanen E., Visuri A., Risto R. & Hosio S. (2022) Comparing consumer grade sleep trackers for research purposes: A field study. Frontiers in Computer Science 4. URL: https://www.frontiersin.org/articles/10.3389/fcomp.2022.971793.

[17] Ibáñez V., Silva J., Navarro E. & Cauli O. (2019) Sleep assessment devices: types, market analysis, and a critical view on accuracy and validation. Expert Review of Medical Devices 16, pp. 1041–1052.

[18] Altini M. & Kinnunen H. (2021) The promise of sleep: A multi-sensor approach for accurate sleep stage detection using the oura ring. Sensors 21, p. 4302.

[19] de Zambotti M., Rosas L., Colrain I.M. & Baker F.C. (2019) The sleep of the ring: Comparison of the oura sleep tracker against polysomnography. Behavioral Sleep Medicine 17, pp. 124–136.

[20] Chee N.I., Ghorbani S., Golkashani H.A., Leong R.L., Ong J.L. & Chee M.W. (2021) Multi-night validation of a sleep tracking ring in adolescents compared with a research actigraph and polysomnography. Nature and Science of Sleep 13, pp. 177–190.

[21] Roberts D.M., Schade M.M., Mathew G.M., Gartenberg D. & Buxton O.M. (2020) Detecting sleep using heart rate and motion data from multisensor consumer-grade wearables, relative to wrist actigraphy and polysomnography. Sleep 43, p. zsaa045.

[22] Arnal P.J., Thorey V., Debellemaniere E., Ballard M.E., Bou Hernandez A., Guillot A., Jourde H., Harris M., Guillard M., Van Beers P. et al. (2020) The dreem headband compared to polysomnography for electroencephalographic signal acquisition and sleep staging. Sleep 43, p. zsaa097.

[23] National Sleep Research Resource (2024). URL: https://sleepdata.org/, accessed: 2025-05-20.

[24] Zhang G.Q., Cui L., Mueller R., Tao S., Kim M., Rueschman M., Mariani S., Mobley D. & Redline S. (2018) The national sleep research resource: towards a sleep data commons. Journal of the American Medical Informatics Association 25, pp. 1351–1358.

[25] Zhang Y., Kim M., Prerau M., Mobley D., Rueschman M., Sparks K., Tully M., Purcell S. & Redline S. (2024) The national sleep research resource: making data findable, accessible, interoperable, reusable and promoting sleep science. Sleep 47, p. zsae088.

[26] Purcell S.M., Manoach D.S., Demanuele C., Cade B.E., Mariani S., Cox R., Panagiotaropoulou G., Saxena R., Pan J.Q., Smoller J.W., Redline S. & Stickgold R. (2017) Characterizing sleep spindles in 11,630 individuals from the national sleep research resource. Nature Communications 8, p. 15930.

[27] Zhang G.Q., Cui L., Mueller R., Tao S., Kim M., Rueschman M., Mariani S., Mobley D. & Redline S. (2016) Scaling up scientific discovery in sleep medicine: the national sleep research resource. Sleep 39, pp. 1151–1164.

[28] Open Humans (2024). URL: `https://www.openhumans.org/`, accessed: 2025-05-20.

[29] Greshake Tzovaras B., Angrist M., Arvai K., Dulaney M., Estrada-Galiñanes V., Gunderson B., Head T., Lewis D., Nov O., Shaer O., Tzovara A., Bobe J. & Ball M.P. (2019) Open humans: A platform for participant-centered research and personal data exploration. GigaScience 8, p. giz076.

[30] Demirci K., Akgönül M. & Akpinar A. (2015) Relationship of smartphone use severity with sleep quality, depression, and anxiety in university students. Journal of Behavioral Addictions 4, pp. 85–92.

[31] Yang J., Fu X., Liao X. & Li Y. (2020) Association of problematic smartphone use with poor sleep quality, depression, and anxiety: A systematic review and meta-analysis. Psychiatry Research 284, p. 112686.

[32] Lin Y.H., Chang L.R., Lee Y.H., Tseng H.W., Kuo T.H. & Chen S.H. (2014) Development and validation of the smartphone addiction inventory (spai). PLOS ONE 9, p. e98312. URL: `https://doi.org/10.1371/journal.pone.0098312`.

[33] Kwon M., Kim D.J., Cho H. & Yang S. (2013) The smartphone addiction scale: Development and validation of a short version for adolescents. PLOS ONE 8, p. e83558. URL: `https://doi.org/10.1371/journal.pone.0083558`.

[34] Fielding R.T. & Taylor R.N. (2000) Architectural Styles and the Design of Network-based Software Architectures. Ph.d. thesis, University of California, Irvine. URL: `https://ics.uci.edu/~fielding/pubs/dissertation/top.htm`, accessed: 2025-04-21.

[35] MDN Web Docs (2024), Javascript guide. URL: `https://developer.mozilla.org/en-US/docs/Web/JavaScript/Guide`, accessed: 2024-04-16.

[36] Async Labs (2023), Vanilla javascript vs react: Choosing the right tool for web development. URL: https://www.asynclabs.co/blog/software-development/vanilla-javascript-vs-react-choosing-the-right-tool-for-web-development/, accessed: 2025-04-22.

[37] DhiWise (2024), Vanilla javascript vs react: Choosing the best approach. URL: https://www.dhiwise.com/post/vanilla-javascript-vs-react-whats-right-for-developers, accessed: 2025-04-22.

[38] Bootstrap (2024), Official documentation. URL: https://getbootstrap.com/docs/5.3/getting-started/introduction/, accessed: 2024-04-16.

[39] Ramírez S. (2019), Fastapi: The modern, fast (high-performance), web framework for building apis with python 3.6+. URL: https://fastapi.tiangolo.com/, accessed: 2025-04-22.

[40] SQLite (2024), About sqlite. URL: https://www.sqlite.org/about.html, accessed: 2025-04-22.

[41] Pydantic (2024), Pydantic documentation. URL: https://docs.pydantic.dev/, accessed: 2025-04-22.

[42] Bayer M. (2024), Sqlalchemy documentation. URL: https://docs.sqlalchemy.org/, accessed: 2025-04-22.