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Improving Occupant's sleep quality with the help of OURA ring and data from Smart Buildings

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Abstract

Well-being is associated with comfort and health, and it represents wellness and quality of life. Sleep quality is an important index when evaluating a person's well-being. KTH Live-in-lab performs Human-building interaction studies to explore the growing potential of how built environments, measured by Schneider Electric (SE), can influence humans and their well-being in their everyday lives. This thesis works as an explorative study of using the OURA ring to evaluate sleep quality for tenants living in KTH LiL. Specifically, this project aims to assess the quality of the data collected from the ring and SE sensors by using Total Data Quality Management (TDQM) and propose a Multilayer perceptron (MLP) model for predicting sleep scores. Results first showed that the OURA ring is an appropriate tool for evaluating sleep quality. Its data passed 11 TDQM's dimensions, including accuracy, objectivity, relevancy, interpretability and understandability. Second, the OURA was able to capture the relationship between sleep quality and building's temperature and humidity through its sleep scores. Results showed that higher sleep scores situated more around the suggested ideal ranges of temperature and humidity. However, some low sleep scores were also situated around these ideal ranges which suggests that an additional study needs to be conducted. Such a study would take in tenants' feedback in order to distinguish sleep scores heavily affected by psychological and/or other factors rather than built environments. Third, we were able to create an MLP model to predict sleep scores based on temperature and humidity values as well as user-related information, like activity rate and total burn. The model had validation and training losses converging at 1.90-2.50. Those low loss rates suggest that the building's temperature and humidity along with information about tenants from the ring can be used to improve the sleep scores. This model can be extended into a recommendation model where buildings' operators and tenants can benefit from. Buildings' operators would get information and recommendations on how to properly administer their buildings to achieve higher well-being for their tenants. Also, tenants would get recommendations on how to increase their sleep scores and, ultimately, their sleep qualities and well-being.

Keywords

Thermal Comfort, Sleep Quality, Well-being, Wearable Devices, Artificial Intelligence, Smart Buildings

Sammanfattning

Välbefinnande är förknippat med komfort och hälsa, och det representerar livskvalitet. Sömnkvalitet är ett viktigt index när man utvärderar människors välbefinnande. KTH Live-in-lab utför interaktionsstudier mellan Människor-Byggnader interaktion för att utforska den växande potentialen för hur byggda miljöer, mätt av Schneider Electric (SE), kan påverka människor och deras välbefinnande i vardagslivet. Denna avhandling fungerar som en explorativ studie av att använda OURA-ringen för att utvärdera sömnkvaliteten för hyresgäster som bor i KTH LiL. Specifikt syftar detta projekt till att bedöma kvaliteten på de data som samlats in från ring- och SE-sensorerna genom att använda Total Data Quality Management (TDQM) och föreslå en Multilayer perceptron (MLP) -modell för att förutsäga sömn resultat. Resultaten visade först att OURA-ringen är ett lämpligt verktyg för att utvärdera sömnkvaliteten. Dess data passerade 11 TDQMs dimensioner, inklusive noggrannhet, objektivitet, relevans, tolkbarhet och förståbarhet. För det andra kunde OURA fånga förhållandet mellan sömnkvalitet och byggnadens temperatur och fuktighet genom sina sömnvärden. Resultaten visade att högre sömn värden ligger mer runt de föreslagna ideala temperatur- och luftfuktighet områdena. Några låga sömn resultat låg dock också runt dessa ideala intervall, vilket tyder på att ytterligare en studie måste genomföras. En sådan studie skulle ta hyresgästernas återkoppling för att urskilja sömn poäng som påverkas starkt av psykologiska och / eller andra faktorer förutom de byggda miljöer. För det tredje kunde vi skapa en MLP-modell för att förutsäga sömn värden baserat på temperatur- och luftfuktighets värden samt använda relaterad information, som aktivitetsgrad och totalt bränn. Modellen hade validering och näringsförluster som konvergerade vid 1,90-2,50. Dessa låga förlust nivåer antyder att byggnadens temperatur och luftfuktighet tillsammans med information om hyresgäster från ringen kan användas för att förbättra sömn värdena. Denna modell kan utvidgas till en rekommendation modell där byggnadens operatörer och hyresgäster kan dra nytta av. Byggnadens operatörer skulle få information och rekommendationer om hur de ska förvalta sina byggnader på rätt sätt för att uppnå högre välbefinnande för sina hyresgäster. Hyresgästerna skulle också få rekommendationer om hur man ökar sina sömn värden och i slutändan deras sömnkvaliteten och välbefinnande.

Nyckelord

Termisk Komfort, Sömnkvalitet, Välbefinnande, Bärbara Enheter, Artificiell Intelligens, Smarta Byggnader

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List of acronyms and abbreviations

1- ICT : Information and communication technology.

2- HBI: Human-Building interaction.

3- KTH LiL: KTH Live-in-Lab.

4- TA: Ambient temperature.

5- IoT: Internet of Things.

6- ANN: artificial neural network.

7- SE: Schneider Electric.

8- HVAC: Human ventilation and air conditioning.

9- TC: Thermal Comfort.

10- PMV: Predicted mean vote.

11- EEG: Electroencephalogram.

12- SWS: Slow-wave Sleep.

13- TDQM: Total Data Quality Management.

14- MLP: Multilayer perceptron.

15- ETL: extract, transform, and load

16- ReLU: Rectified Linear Activation Function

16- SGD: Stochastic Gradient Descent

17- RHR: Resting heart rate

18- HRV: Heart rate variability

19- VC: Vapnik–Chervonenkis

20- NW: Number of weights

21- AI: Artificial Intelligence

1 Introduction

Information and communication technology (ICT) has many applications nowadays, and it plays a significant role in enhancing people's lives. It has considerable contributions in many fields, like education, medicine, transportation, and agriculture. ICT also contributes to the buildings' sector. A building's life cycle can be automated with ICT devices by integrating leading technologies in the systems and operations that make up the entire building. These types of buildings are typically referred to as "Smart Buildings". A building generally requires many technologies to attain the "Smart Building" property; such technologies include human-computer algorithms, big data analytics, sensors, and cloud computing [1].

Furthermore, a building is built to perform spatial and physical functionalities that hold social values. The physical relates to the shaping and decorations, and the other relates to the spatial arrangement of activities and relationships [2]. Taking that in mind, one can use the human-building interaction (HBI) to design the appropriate building. HBI refers to the interface between tenants and their surrounding buildings' spaces by focusing on the functionalities' interactions and interconnections [3]. So, the Human-building interaction study provides interactive opportunities for tenants to form spatial, physical, and social functionalities in their built environment [4].

KTH Live-in-Lab (LiL) performs Human-building interaction studies to explore the growing potential of how the built environment can influence humans in their everyday lives. It uses smart buildings to create test-beds that accelerate innovation in the construction sector and reduce the lead time between research results and market introduction. KTH LiL puts the occupants' in the center of its focus when implementing new test-beds, which allows it to study the end-users and their surroundings' built environment. The occupants' built environment at KTH LiL are measured by using multiple Schneider Electric (SE) sensors. However, when trying to thrive for occupants' well-being and comfort, access to their body signals is essential. That is where ICT-enabled wearable devices come into play.

SE wanted to contribute to a more innovative construction sector and expand its cooperation with the KTH LiL in 2019. Schneider Electric will actively participate in research and development at the lab for three years by contributing to consulting, services, and technology. All the environmental parameters that are used in this project are taken from SE sensors, which are monitored inside KTH LiL buildings. [15]

In the general press, and in guidelines and recommendations, well-being (also spelled wellbeing or well being) is often simplistically intended as synonymous with wellness, happiness, and quality of life, or associated with comfort and health [5]. Sleep quality is one of the most important indices for evaluating human well-being. The majority of the previous studies focused on two factors: 1. The physical disturbances such as the mobile phone and acoustic noises in the surrounding area. 2. Medical issues such as sleep apnea and psychiatric disorders. A few pieces of research considered environmental factors such as ambient temperature (TA), relative humidity, CO2 levels. Previously, studying those factors was challenging as it required expensive equipment and measurement tools. Nowadays, with the emergence of the internet of things (IoT), wearable devices, and artificial intelligence, it is possible to investigate the impact of environmental factors. Therefore, we will study the possibility of using collected data from small wearable devices to improve tenant's sleep quality by achieving ideal surrounding built environment.

1.1 Problem

Wearable devices are small, technical devices that provide informative information about the human body. They come in different shapes and are commercialized for their specific objectives. For example, wristbands and straps are used for fitness tracking by monitoring vital signs and activity rates. Recently, there has been an increase in wearable devices that provide precise and detailed physiological information about the human body, which shows hidden knowledge about the body that could easily contribute to better wellbeing. The OURA Ring is one of those wearable devices that explicitly monitors sleep and activity rate qualities. OURA Ring provides informative data about users' daily health. It analyzes the users by measuring and detecting their body signals. The ring uses the data to calculate, with embedded algorithms, the qualities of sleep and activity rates. KTH LiL requires a passive way to get personal body-related information about their tenants in order for them to use the human-building interaction methods to adjust the built environment to increase the wellbeing of their tenants. In this study, KTH LiL addresses wellbeing by studying the sleep quality of tenants, and the OURA ring has been chosen for this study because of its commercialized high-quality nighttime data. Moreover, there is a lack of sleep quality research that does not depend on users' feedback, controlled environments, or expensive polysomnography. The objective of this study is to address the following research questions:

- What are the possibilities and limitations of measuring sleep quality from built environments and the OURA ring in the real-life context?
- Is it possible to use artificial neural networks (ANNs) for predicting sleep qualities for the tenants?
- Can the data from the OURA ring and SE sensors be used for providing personalized instructions for its users to increase their sleep qualities?

1.2 Purpose

The purpose of the degree project is to work as an explorative study for the real-context-driven research of sleep quality at KTH Live-in-Lab using the OURA ring. This thesis will benefit future researchers working on physiological measurement-based approaches for human-centered sleep quality by giving them a headstart on what the data collected from the OURA ring can provide and the potential limitations. This project will also serve different stakeholders in the real estate industry and the smart buildings industry. For example, this will help building owners by providing better thermal comfort solutions and giving enough information about energy consumption inside the building. It will also serve the occupant as a stakeholder by maintaining sleep quality and as a result improving their wellbeing in general. However, there are some ethical concerns regarding the data being collected, and there might also be social concerns regarding the impact of those systems on the tenant's lifestyle.

1.3 Goals

The goals of this project are twofold:

1. Assess the quality of the data collected from the OURA ring.
2. Investigate whether the data from OURA can be used in combination with the data from SE in KTH LiL to create an appropriate model for sleep quality evaluation.

These goals have been divided into the following sub-goals:

1. **Data storage:** Building a data storage with an appropriate data structure from the OURA ring and Schneider Electric data.
2. **Data quality assessment:** What are the possibilities and limitations of measuring sleep quality in a real-life context with the use of the OURA ring?
3. **Modeling:** Building an ANN for improving sleep quality with the OURA ring and SE sensors' data based on the possibilities and limitations concluded about the data from sub-goal 2.

The final deliverables we anticipate from this project is to have a complete functioning database that has all the information we need. The database should be well organized and easy to access. We also should have the model completely functioning and delivering useful results or information on why this approach might (not) work.

1.4 Delimitations

We have some limitations in the thesis project. First, we do not have any feedback from the users. Second, we will not test the modeled algorithm in real-time applications. Third, our modeled algorithm will be limited to predicting a user's upcoming sleep score. Fourth, we have a limited amount of data due to a lack of participants. Furthermore, the delimitations of the thesis project are the psychological and emotional effects on sleep, non-nighttime sleep, and health issues. Psychological, emotional, and health issues have huge effects on sleep quality. Since we will not be taking feedback from users, it will be hard to notice those effects. Moreover, non-nighttime sleep is of no importance to us since our test subjects follow the regular sleep schedule (nighttime sleep).

1.5 Structure of this report

Chapter 2 presents relevant background information about thermal comfort, Human, ventilation and air conditioning (HVAC) , sleep quality, wearables and OURA ring, and KTH Live-in-Lab.

Chapter 3 presents the methodology used to solve the problem.

Chapter 4 presents the implementation, describes the algorithm, and discusses the internal structure of the project.

Chapter 5 presents the results and analyzes them.

We conclude the discussion in Chapter 6 by presenting the final answers to our research questions. We also present the basis and foundation for any future work that's being conducted in this area.

2 Background

This chapter provides basic background information regarding thermal comfort and HVAC systems. Additionally, it illustrates the importance of sleep quality and the impacts of thermal comfort on it. It provides a brief description of IoT, artificial intelligence, smart systems, and wearable devices. Finally, it introduces the KTH LiL.

2.1 Thermal Comfort

Thermal comfort (TC) is the ideal point (sometimes called the equilibrium point) of the surrounding environment's thermal conditions, giving humans the best sleeping quality. It is evaluated directly based on the tenant's feedback and feelings. There exist many models to evaluate the TC of a human being. Among these is the well-known predicted mean vote (PMV).

PMV is an index that predicts the mean value of votes of a large group of people. The prediction is made on a seven-point thermal sensation scale, ranging from +3 (hot) to -3 (cold) [6]

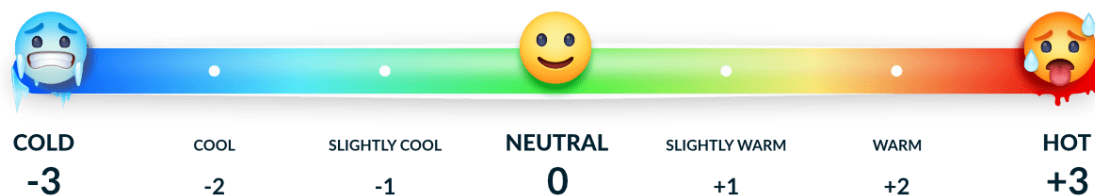


Figure 2.1: seven-point thermal sensation scale

However, regardless of the applied model, there are always six parameters that must be addressed when evaluating thermal comfort. Those parameters are divided into:

- 1- Individual (directly related to the person) refers to the metabolic rate and clothes insulation level.
- 2 Environmental (not affected by the person's state) refers to air temperature, radiant temperature, relative humidity, and airspeed. Some models add other secondary factors as well. [6]

Table 2.1: primary factors that are taken into account when evaluating thermal comfort

Characteristics	Description
Air temperature	The temperature of the atmosphere, it's a measure of how cold or hot the surrounding air is. [7]
Relative humidity	It is a measure of the amount of water vapor in the air to the total amount that can ever exist in the air. Water vapor / Total possible water vapor RELATIVE to air temperature. [8]
Mean Radiant temperature	MRT represents the mean of the radiant temperatures of the enclosing surfaces of a space, which is determined by the emissivity and the temperature of the surfaces.[45]
Air speed (Air movement)	This is the rate of spatial change of air in a space, which is used to calculate convective heat transfer and thus changes the comfort zone [45]
Metabolic rate	Metabolic rate is the rate of energy production of the body, which varies for different activities.[45]
Clothing insulation level	Clothing is probably the most important variable in terms of adaptation to a thermal environment, and this means that acting on the clothing level may be very effective to reduce energy consumption. [45]

2.1.1 HVAC Systems

The heating, ventilation, and air conditioning (HVAC) represent mechanical and smart systems monitored inside buildings. These systems provide the occupants' desired environmental conditions inside of their homes. The buildings are often provided with heating, ventilation, cooling, and air conditioning equipment. Usually, the equipment is located in a dedicated room inside the building (local HVAC systems) or outside the building (central HVAC systems). [9].

2.2 Sleep Quality

There is no quantitative definition for sleep quality, but, in general, it refers to how well a person slept. For example, sometimes we wake up having bad mornings or feel exhausted even though we slept enough hours to feel energetic. The reason is that we might have had inadequate sleep quality. Studies show that good sleep quality results in a lower risk of heart disease, lower inflammation, lower depression, and more robust immune systems. [10]

In terms of this research, the measure of sleep quality that we will use is the one provided by OURA API (sleep score). OURA analyzes the body dynamics such as resting heart rate (RHR), respiration rate, different sleep cycles (light, deep, and REM), and a few other factors to determine how well you sleep. OURA uses this metric to guide people toward better health and mental conditions; the higher this score is, the more energetic and ready the person is for the next day. In general, a sleep score that is above 70 is considered a good score. However, OURA does not provide any information about how the person should adjust their surrounding environmental parameters for achieving better sleep scores. The only information provided by their app and algorithm to increase one's sleep score is to set a consistent sleeping time and sleep duration for the ring-wearer.

[11]

2.3 Wearables and The OURA ring

Wearables are smart and small technical devices that can be worn on the body or can be attached to clothes. They are often integrated with multiple sensors responsible for providing informative information such as heart rate, blood pressure, respiration rate, and cardio-related parameters. The wearable devices' technology comes in different shapes and has different purposes. For example, they can be watches, rings, or belts. In addition, a single device has several sensors to measure different parameters. Some purposes for these devices are athletic, medical, educational, entertainment, and business.

[12]

The OURA ring is a smart ring that mainly aims to maintain personal health through sleep monitoring. It has a regular ring shape, and the following sensors:

- **NTC Temperature Sensors:** this sensor is responsible for measuring the body temperature directly from the skin. OURA claims that by using these sensors they are able to get accurate measurements of the person's body temperature. According to OURA, this is a better approach than estimating it from the surroundings as many other companies do.
- OURA uses a **3D accelerometer** to measure different activity and movement-related parameters, and they combine these parameters with the profile information that the user provided to get accurate analysis and data about energy expenditure and movement (steps, miles).
- **Infrared light sensor:** this sensor measures the respiratory rate, and the reason that OURA uses this sensor is due to its higher accuracy compared to other sensors like green light LEDs. [13]



Figure 2.3: a picture of the ring with a clear view on the three mentioned sensors.

2.4 KTH Live-in lab

“Testbeds for innovation in building and housing sector”

KTH LiL is a multiple testbed platform that offers a full-scale test environment ranging from buildings and installations to housing and management organizations. They perform tests for products and services by providing the opportunity to conduct tests in actual buildings. As a result, KTH LiL helps build a strong foundation for changing the rules in the industry. In Addition, it ensures that companies can test their products in real environments and test how different components of their products are affected by/affecting the results.

They aim to achieve sustainable development in the real-estate sector and accelerate the innovation and rate of introduction to new competitive products in the real estate and construction sector. As KTH is the Nordic’s leading tech university and with the high-quality research that the university provides, LiL can provide companies and students with high-quality research relevant to their tests and projects.

[14]

2.5 Related Work

2.5.1 Sensing occupant's thermal comfort using wearable technology

Both the accuracy of the data provided and the possibility of achieving TC with the use of wearable devices have been investigated. During the construction research congress 2016, 4 researchers published a research named: sensing occupant's thermal comfort using wearable technology [16]. Their main objective was to investigate the feasibility of achieving occupant's thermal comfort using wearable devices. They conducted an explanatory pilot study to achieve their goal, they used an application for collecting data in indoor environmental conditions, they also used wristband wearable devices to measure the accuracy of the data collected by the mobile phone. The study took place in a present conditional laboratory at the University of Colorado Denver.

They used different models to evaluate different results, however, they found that the model that achieved the best results; is a model that used the following parameters:

Air temperature, square root of the summation of perspiration and air temperature, summation of perspiration and relative humidity, skin temperature, and heart rate.

However they also realized that the accuracy of the results is questionable and they suggested a better choice for wearables and sensors in future studies, but they found it possible to estimate, measure, and achieve better thermal comfort by using wearable devices.

The accuracy of the investigated wearable devices also depends on the year at which the study was conducted. This study is from 2016, so wearable devices could, and probably, have become more accurate at providing information and physiological data about their users.

2.5.2 Experimental study on thermal comfort of sleeping people at different air temperatures

Air temperature is an important environmental contributor that affects sleep quality. A study was made on the effects of air temperature on sleep quality and maintaining thermal comfort of sleeping people [17]. The study conducted questionnaires and used

electroencephalogram (EEG) to evaluate sleep quality, and it used subjective assessments for thermal comfort before and after bedtime. The study concluded that the subjects experienced lower periods of slow-wave sleep (SWS), took longer time to fall asleep, and answered lower in the subjective assessment when bedroom temperatures were at 23° or 30° C compared to 26° C. The study also found that the subjects' skin temperatures increased with bedroom temperatures and fluctuated during sleep time and that their sleep qualities were sensitive to the change in air temperature. It is obvious from this study and many more that air temperature is an important parameter and must be taken into consideration when researching sleep quality and ways to improve it.

2.5.3 Effects of thermal environment on sleep and circadian rhythm

Another study was conducted on the effects of thermal environment on sleep and the main results were [18]:

Heat Exposure

In situations where bed covers and clothing are used, heat exposure increases wakefulness and decreases SWS (Deep sleep) and REM during the initial segments rather than the later segments of sleep. One possible explanation for this is that sleep disruption in the early segments could lead to increased demand for sleep, which may overcome the sensation of thermal comfort in the later segments of sleep. Heat exposure disruptions do not adapt even after several days of continuous daytime and nocturnal heat exposures. Heat increase in the surrounding environment suppresses the decrease in the body's core temperature, which leads to disruptions in sleep in the early segments. It also increases the skin temperature and amount of sweat loss during sleep.

Ambient temperature (TA) cycles during sleep could affect the core temperature of the person asleep. Decreased Ta occurring a few hours before and after sleep onset and increased TA occurring around wake-up time increases the decline in body's core temperature and advances its nadir compared to constant TA. The REM cycle length is also affected by the TA. The REM is delayed in lower TA compared to higher TA during sleep.

Humidity

Humid heat exposure increases wakefulness, decreases SWS and REM sleep, and suppresses decreases in body's core temperature, but skin temperature and whole-body sweat loss do not get affected by humid heat. Decreased humidity allows sweat to evaporate, causing the dissipation of heat. Increased humidity, on the other hand, prevents the evaporation of sweat, which causes the skin to remain wet. The dripping sweat and increased skin wetness decrease the sweat response due to hydromeiosis preventing dehydration.

Humid heat exposure in the initial segment of sleep decreases the SWS and increases wakefulness in both segments. The decrease in SWS in the first segment causes an increase in SWS in the later segment of sleep. This means that the humid heat exposure in the initial segments causes the change in SWS polarity during sleep.

3 Methodology

We used different methods, and programs to conduct our research. First, the data storage part was done using Node.js, excel, and MongoDB. Second, data quality analysis was done using Excel, Matlab, and Total Data Quality Management method (TDQM). Third, data modelling was done with Python, MongoDB, and the multilayer perceptron model.

The choice of these methods was made based on several factors, first we realized that the TDQM is a well-structured method for data assessment and thus it is a convenient choice for our project. Secondly, we had to choose a method that provides us with satisfying results in terms of data storage and at the same time it should not be a complex method, so MongoDB was the preferred choice here. Finally, the choice of python was based on the fact that it has many useful libraries for our project.

3.1 Research Process

In order to research our problem, KTH live-in-lab provided us with a collection of data about three different users. It consisted of data from the wearable OURA ring and the Schneider electric sensors located in their apartments. The OURA ring provided the physiological data about the users, and the SE sensors provided the building's environmental data.

The data was tabular formatted and saved as multiple csv and xlsx files, which we imported to excel. This format was convenient for us because it was well-structured and easy to understand. The data of the OURA ring and SE sensors contained some irrelevant information. We removed them and saved only the relevant parts. So, we created a database where we saved only the relevant data from these csv and xlsx files.

After creating a database with a suitable data structure, we moved to the data quality assessment and data modelling stages. Those are the main stages for our explorative study. We assessed the quality of the data, defined limitations and boundaries, built hypotheses, and suggested a deep artificial neural network model.

3.2 Research phases

An overview of our research phases can be found in Figure 3.2.1. *The general literature review* includes the pre-research and study done at the beginning of the thesis about wearable devices, OURA ring, KTH live-in-lab, and sleep quality. *Context analysis* includes the analysis of infrastructure, wearable devices, privacy and ethics, and market readiness that facilitate the environment in which this thesis research is handled. *System boundaries* is the phase where the data quality management was performed. *Specific literature review, experiment design, and results evaluation* include the phases where the data modelling was done. More about those last four phases are talked about in sections 4 and 5.

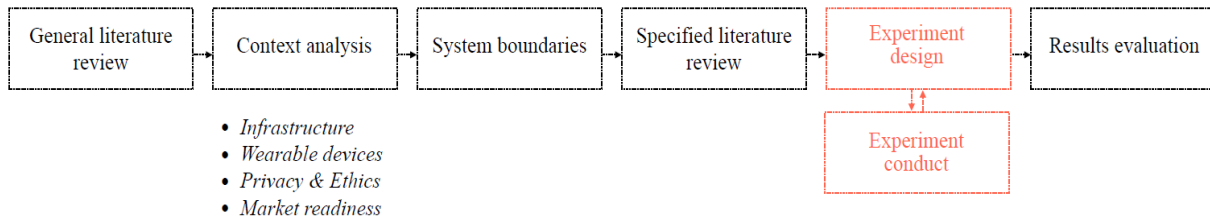


Figure 3.2.1: Research phases.

3.3 Sampling, Methods and Programming

3.3.1 Sampling

Two types of data are collected in this thesis. The first is building environment data collected from SE sensors in KTH live-in lab buildings in the form of xlsx sheets. The second is physiological data collected from the OURA rings of KTH LiL apartments' tenants in the form of csv sheets. The data was collected from the SE sensors installed inside the KTH live-in lab's buildings and the OURA ring worn by users in these apartments. To follow the GDPR data protection rules, the tenants agreed in a signed form to use their data for a specified number of months, eliminating any possibilities of ethical or social violations. Furthermore, the data was being collected passively, which means there were no physical monitoring and/or tests performed on the tenants. Thus, it does not have any impact on their normal lives.

3.3.2 MongoDB

When implementing the database, we decided on using a NoSQL database, specifically "MongoDB". MongoDB stores data in JSON-like documents, which means the fields can vary between documents, and their structure is flexible and can be changed at any time. This structure allows for horizontal scalability. That helps in accommodating large databases, which are convenient when working with large amounts of users and building data. The documents consist of pairs of fields and values. The values can be of any type (string, number, Booleans, and arrays). Those documents are stored in collections similar to tables in relational databases (e.g., SQL).

3.3.3 TDQM: Total Data Quality Management

The methodology selected for data quality assessments of the OURA ring and the SE sensors is TDQM. This methodology is considered a result of the idea of “fitness for use” [Wang & Strong 1996]. This method looks at the data as a product. All products have life cycles, and so does the data. The method is relatively simple, and the following basic processes can summarise it:

- Define: this process identifies the quality of information requested by information consumers. It also analyses the information life cycle that characterizes the production process. In our assessment, this process will identify the metrics and desired information that could potentially be used for the modeling stage of our research.
- Measure: in this phase, we will measure the different data we have according to the metrics and desired information we identified in the previous process. That allows us to analyze and confirm what parts of our data can be used and what can not.
- Analyze: This is a fundamental part of the assessment process. In this step, we analyze the results we got from the previous steps. In addition, this phase helps us identify the reasons behind the different data errors, which is essential for the improvement process.
- Improve: This prioritizes the wrong data and starts by developing a plan to improve and correct these parts of the data. Thus TDQM is a methodology that focuses both on data quality assessment and data improvement. [19]

3.3.4 Multilayer perceptron (MLP)

MLP is a feed-forward deep artificial neural network, and it is applied to supervised learning. The uses of MLP are pattern classification, recognition, prediction, and approximation. It consists of three layers: input layer, hidden layers, and output layer, as shown in figure 3.3.2. The hidden layers' number is arbitrary, and they are the computational engine for MLP. As for the output layer, it is responsible for performing the required tasks signaled in the input layer. The model trains each neuron with a backpropagation algorithm. MLP was chosen for a few reasons. First, MLP can learn the training data's representation and how to best relate it to the output variables. Second, It is said that MLP can produce useful predictions from relatively small training data (≤ 100). [20] Third, it is one of the simpler machine learning models to use. And, given our limited time in this project, we appreciate uncomplicated algorithms.[21]

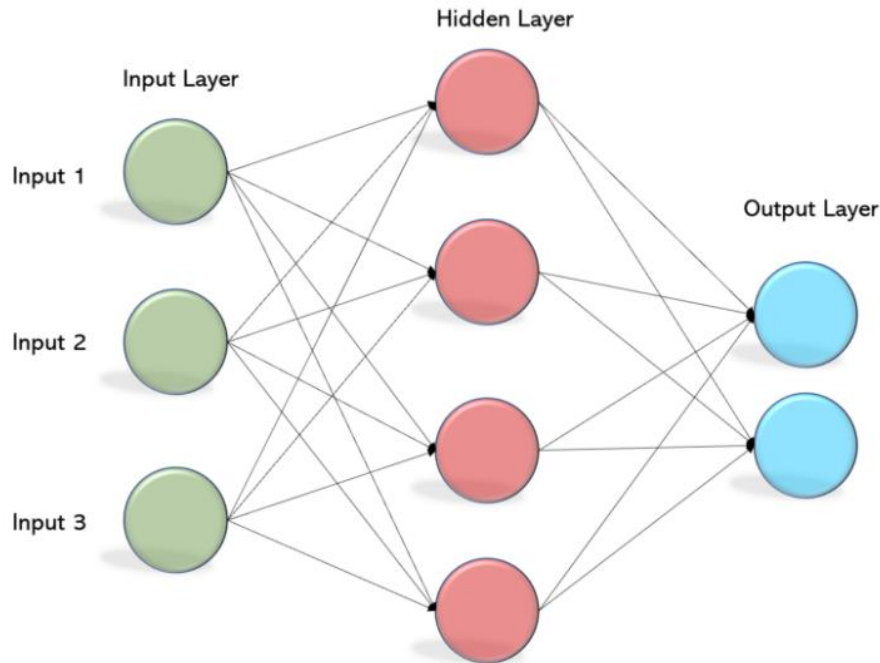


Figure 3.3.2: Multilayer perceptron model

3.3.5 Programming

A few programming languages were used to conduct this research, but most were used for limited and short tasks.

Firstly, Matlab was used for graphing boxplots, line plots, and distribution functions to provide some analysis and quality checks for the data. Choosing Matlab was because we had some experience with it, and it was readily available to us. Matlab is also easy to use with a lot of functionalities, which makes it convenient for us. Secondly, Node.js was used when implementing MongoDB. The reason for the choice here is similar to Matlab's; we were familiar with Node.js. Thirdly, Python was used for modeling the deep artificial neural network. This language was chosen for modeling because Python provides much assistance for machine learning algorithms. The simplicity of the language and assisting libraries made Python the best choice for the programming language. [22] As for choosing the libraries, we used Keras from Tensorflow. Tensorflow is a free and open-source machine learning library. It provides a comprehensive, flexible ecosystem of tools, libraries, and community resources that lets researchers push the state-of-the-art in ML and developers quickly build and deploy ML-powered applications. [23] Keras, on the other hand, is a high-level API. Keras follows best practices for reducing cognitive load: it offers consistent and straightforward APIs, minimizes the number of user actions required for everyday use cases, and it provides clear & actionable error messages. It also has extensive documentation and developer guides. Keras is specially designed for assisting the build and deployment of neural networks, and since our approach is an MLP algorithm. So, Keras was the best library to use. [24]

4 Implementation

4.1 Database

Since the collected data was in csv and xlsx sheets, creating a database with an appropriate data structure was essential. Creating the database at the beginning of the project helped facilitate the important fields and made them more easily accessible in the other stages of the thesis. The data structure was chosen to implement two properties: 1- Separating tenants from each other. 2- Days of each tenant are separated from each other. This implementation allowed for straightforward storage and/or retrieval of data. This stage can be viewed as an extract, transform, and load (ETL) pipeline, and it was mainly done in Node.js and MongoDB. The overview of the ETL pipeline can be found in figure 4.1

4.1.1 Extract

The data was extracted from SE sensors in the form of multiple xlsx sheets. Each sheet contains ~1-2 months of a specific building parameter (humidity, temperature, and CO2 levels). As for the data extracted from the OURA rings, it is in the form of csv sheets. Each sheet contains ~1-2 months of physiological information of a tenant. The retrieved sheets were then saved on our private computers and were ready for the transform phase.

4.1.2 Transform

This phase consisted of transforming the data to follow our desired data structure and manually checking/analyzing the transformed data for any errors. The data structure is in the form of collections that hold multiple documents. A collection was made in association with each tenant. Each collection holds data related to the tenant in the form of JSON documents. Each of those documents holds one day's worth of information about the tenant. A document then has the following structure:

```
{
  Date: number(day:month:year) e.g. 01/05/2020
  Sleep Score: number e.g. 93
  TempStart: number e.g. 50
  Activity Score: double e.g. 13.75
  Readiness Score: number e.g. 100
  RelativeHumid: number e.g. 90
  RestfulScore: number e.g. 80
  LatencyScore: number e.g. 82
  TotalBurn: number e.g. 2940
  TotalSleep: number e.g. 112233
}
```

Mongoose schema was used to define the documents' structure and their default values. MongoDB will automatically generate an ObjectId for every document in a collection. Although ObjectIDs were not necessarily useful for our research, we used them to keep track of critical or issues-generating days/documents.

4.1.3 Load

The transformed data was loaded in our MongoDB database, which is being hosted on our private computers. For security reasons, no one was allowed to view this database except for project members and supervisors.

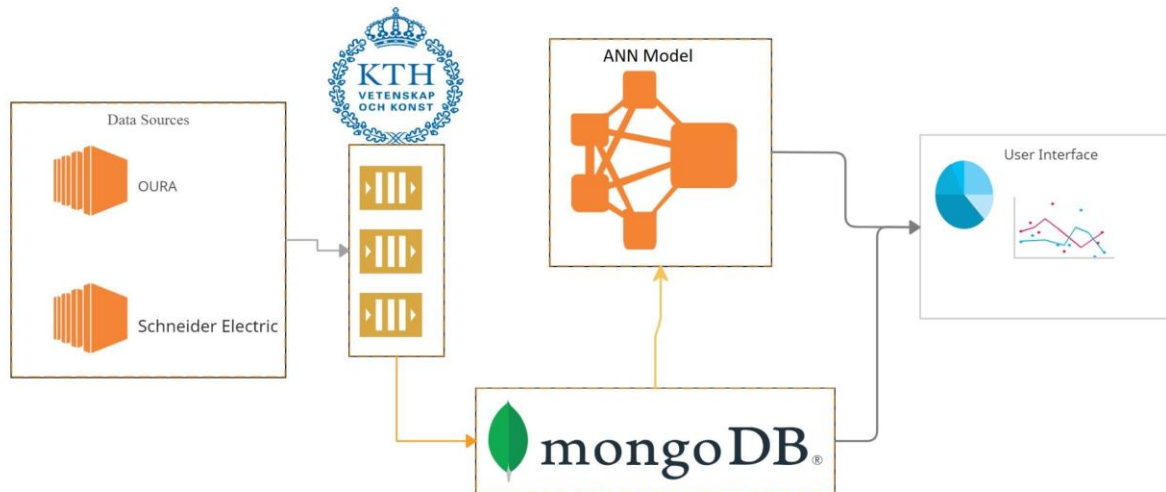


Figure 4.1: ETL data pipeline during the different stages of this project

4.2 TDQM

As mentioned in the Methodology section in 3.3.3, we have chosen to apply the total data quality management method to our data. This section will explain how and what exactly we did in terms of the data we have and the scope of this project. For this project, we are dealing with two different sources of data. The first comes from the ring and the second comes from the SE sensors placed in KTH Live-in-lab buildings.

As presented in section 3.3.3 this method starts by defining the metrics and dimensions that are important for the later stages (Measuring, analysing). These dimensions will be the same for both data sources. Evaluation for the data and assessment will be based on these dimensions; see table 4.2

Table 4.2.1: Definitions of metrics and dimensions

Dimension	Definition
Believability	The extent to which data is regarded as true and credible
Accuracy	Syntactic accuracy: it is measured as the distance between the value stored in the database and the correct one
Objectivity	The extent to which data is unbiased, unprejudiced, and impartial
Reputation	The extent to which data is highly regarded in terms of its source or content.

Relevancy	The extent to which data is applicable and helpful for the task at hand
Timeliness	The extent to which the data is sufficiently up-to-date for the task at hand.
Completeness	The extent to which data is not missing and is of sufficient breadth and depth for the task at hand
Appropriate amount of data	The extent to which the volume of data is appropriate for the task at hand
Interpretability	The extent to which data is in appropriate language, symbols, and units, and the definitions are clear
Understandability	The extent to which data is easily comprehended.
Consistency representation	The extent of which data is presented in the same format.
Concise Representation	The extent to which data is compactly represented.
Accessibility	The extent to which the data is available, or easily and quickly retrievable.
Access Security	The extent to which access to data is restricted appropriately to maintain its security.

The Dimensions above have been mentioned and categorized in [Wang and Strong 1996 : 20]

Table 4.2.2: Data quality dimensions [Wang & Strong, 1996:20]

Data quality category	Data quality dimensions
Intrinsic data quality	Believability, Accuracy, Objectivity, Reputation
Contextual data quality	Value-added, Relevancy, Timeliness, Completeness, Appropriate amount of data.
Representational data quality	Interpretability, Ease of understanding, Representation consistency, Concise representation.
Accessibility data quality	Accessibility, Access security.

As for the measuring stage, the process was different for the two data sources, so each will be discussed separately.

- **From the OURA:** To collect data (Measuring), we distributed sample rings to students living in KTH LIL apartments. The students wore their rings for the agreed-on period. The measurement was done entirely by using the ring's sensors, and they were not manually manipulated.

- **From SE sensors:** This data is automatically measured by the different sensors placed inside the KTH Live-in-lab buildings. Since we are not the main responsible for the measurement of this data, we do not have enough information about what kinds of sensors are used for measuring. However, we use the references provided by SE on their website for assessing the accuracy of these sensors.

The next step was to analyze the data. Each data sample was analyzed separately by examining and studying examples. The analysis and examination were done by applying the different definitions to the different dimensions we have. The dimensions then were categorized into the following assessments:

- **Approved:** This indicates that the data passed the dimension according to the established definition.
- **Rejected:** This indicates that the data did not pass the test, and it must be modified if the parameter is to be used in the modeling stage.
- **NA:** this means that not enough information was found for assessing the dimensions, but it is OK to proceed with using this data without any further improvements.

No improvements were done on any of the parameters in the data since that lied beyond the scope of this thesis.

4.3 Modelling

In this chapter, we are explaining the model we used and how we developed and applied it. The third sub-goal of this project, described in section 1.3, was to create a model and a good algorithm for improving tenant's sleep quality by adjusting the built environment. However, we were constrained by the amount of data provided to us, and training a model requires a lot of data. For that reason, we decided that we will not personalize the model, which means our model will be trained on a combination of all the data from all tenants. So for the training stage, we merged the data into one set, which gave us a big enough dataset to train the model on. Moreover, after conducting a heavy literature review on this matter, we found that the best and most suitable model choice would be the deep learning model "Multilayer perceptron". For more details and the motivation of our choice, see section 3.3.4.

After we decided on the algorithm, it was time to prepare the data that is being used. The loaded data is in the form of an array of JSON elements. Each element has the same structure as described in section 4.1. For preparation, we had to split the data into two types of NumPy arrays: input and output variables. Both types would then be fed into the model. The variables are summarized as follows:

Input variables:

1. Temperature of the room
2. Relative humidity of the room
3. Total time spent sleeping
4. Activity score
5. Readiness score
6. Restfulness score

7. Sleep Latency score
8. Total Burn

Output variable

1. Sleep score

So, from the model's point of view, there are eight input variables and one output variable. The model will be learning how to map the input variables to the output variable, which can be summarized as $y=f(x)$.

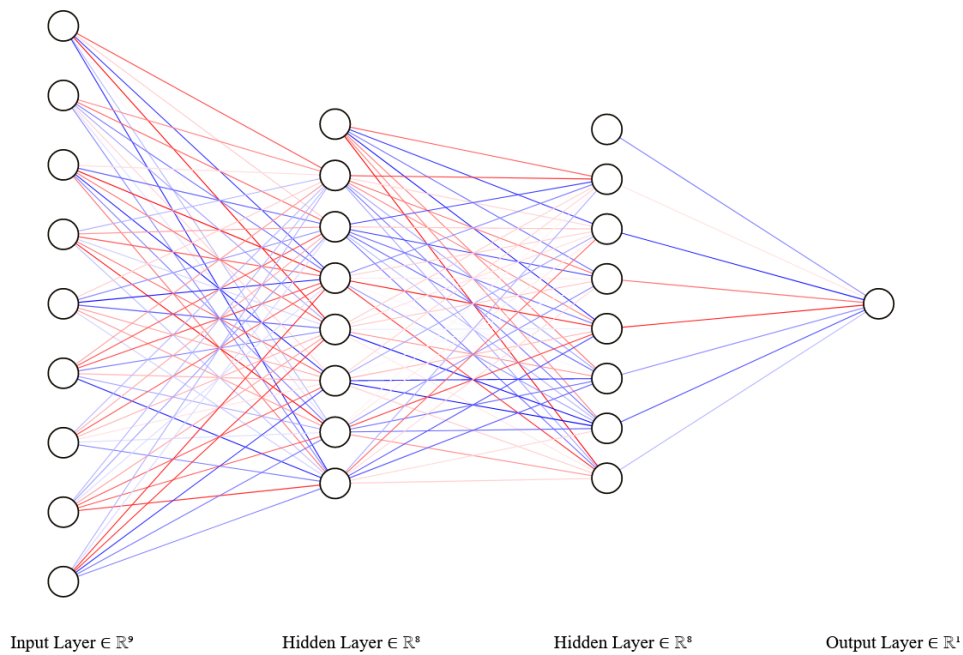


Figure 4.3.1: The ANN structure of our model.

Modelling was done in three stages; defining, compiling, and fitting (training) the model. [25]

The first step was to decide the shape and identity of our model; by this, we mean the number of layers, the number of neurons inside each layer, and activation functions. Based on the literature review we conducted, there was no specific approach for deciding how deep the model should be, i.e., the number of hidden layers. The ideal approach adopted by the majority of developers is the trial-error procedure [26]. After we conducted many trials with different numbers of activation layers, we found that choosing two hidden layers is ideal for our problem, and it gave us the best results. As for the neurons, their quantity differs from layer to layer. First, the input layer takes in rows of input data with nine variables. Then, the first and second hidden layers have eight neurons (nodes) each. Finally, the output layer has only one neuron; the predicted sleep score. Furthermore, the activation function for the input and hidden layers was the Rectified Linear Activation Function (ReLU).

ReLU is a simple function that returns the input directly if it is positive and returns 0.0 otherwise. This simplicity makes a model easier to train and achieve better performance. In addition, ReLU is linear for positive inputs, and it is nonlinear for negative or 0.0 inputs (all nonpositive inputs are mapped to 0.0). This property is desirable when training a neural network model using stochastic gradient descent with backpropagation of errors, as it allows the model to learn more complex relationships in the data. [27]

ReLU Function

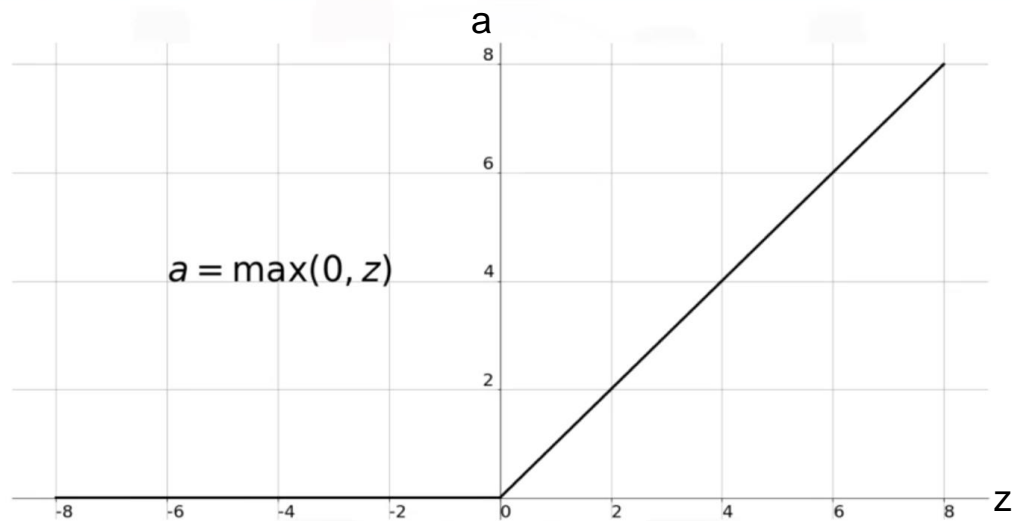


Figure 4.3.2: Visual representation of the RELU activation function.

Next, the defined model was compiled. A few parameters need to be specified when compiling a model. These parameters are the loss function, optimizer, and metrics. Firstly, the loss function chosen was the mean absolute error. Mean Absolute Error is a type of regression loss function, which is appropriate in this case because the model is ultimately trying to find the relationship between the input and output to predict a real-valued quantity. [28] It is calculated as the average of the absolute difference between the actual and predicted values. Secondly, the optimizer chosen was Adam's version of stochastic gradient descent (SGD). When training the neurons' weights iteratively, this version of SGD uses moving averages of both the gradients and their second moments. Adam's optimizer was chosen for our model because it is computationally efficient, requires little memory, and it works well with very noisy and sparse gradients [29]. Thirdly, in order to judge the accuracy performance of our model, we chose the accuracy metric. The accuracy metric's values are viewed when fitting the data and evaluating the model, but they are not used during the training. [30]

Finally, fitting (or training) is the last step required before evaluating the model to predict the sleep scores. Other than the validation set used for testing, sizes for epoch and batch needed to be set in this step. Training the model happens over epochs, which are divided into batches. An epoch refers to one passing through all the days in our dataset, while a batch refers to a number of samples that the model

works through before updating its internal parameters. As with the number of hidden layers, choosing the appropriate number of epochs and batches is a trial-error procedure. For the epochs, we kept increasing their size until we found the range in which the model got overfitted. Overfitting occurs when the model by-hearts the dataset, which means the model memorized the data instead of learning it. That range is noticeable by plotting the validation and training loss, and looking for when the validation loss starts to slightly increase instead of decrease. For our case, that range was around >100 . [31] As for the batch size, we came to choose a low size. Generally a large batch size is recommended for high learning rates, and small batch size is recommended for lower learning rates. Since we are using the default keras learning rate of 0.01, we decided to use a low batch size of 30. [32]

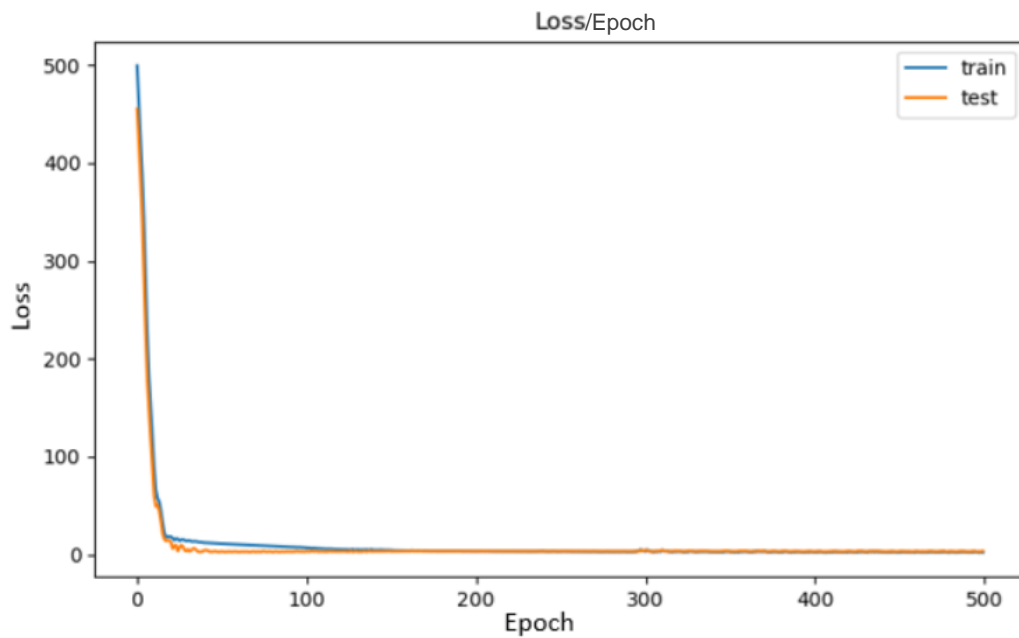


Figure 4.3.3: Loss/Epoch testing results.

5 Results and Analysis

The results are separated into two sections, the data quality management results and the modelling results.

5.1 Data Quality Assessment Results (TDQM)

As described in section 3.3.3 the method we chose for our data assessment is TDQM, the method aims for validating many aspects of the data such as validity, quality, believability, security, etc.

When assessing each dimension, we had to follow different approaches on different dimensions.

Believability: When assessing the believability of the data, we had to take into consideration many things, whether the data values are reasonable, have the values been manipulated before we got them or not. In case of the data from the OURA ring, the data was extracted directly from the OURA database, and since the study is about the OURA ring, so we had to approve the believability of the data coming from OURA, also we are aware that the data was extracted using an API developed by two technicians from KTH, we had the possibility to speak to one of them, and according to him, the data was not manipulated or changed at all. The other source of data we had, is the data from the SE sensors, this data is measured and stored inside KTH servers, The data was sent to us by one of the main supervisors on this project, and thus it's trustworthy and we approved the believability of the data from SE as well.

Accuracy: to assess this dimension, we had to do heavy research, our main sources for information were the official websites provided by both companies OURA and SE. OURA in their website provides plenty of information about the accuracy of their sensors and how accurate the values for each parameter is. However, after assessing the accuracy of each parameter individually, we were able to identify which parameter is accepted and which is not.

- **Sleep Score:** OURA states in their website that the sleep score is calculated based on many parameters including your resting heart rate (RHR), heart rate variability (HRV), body temperature, respiratory rate, and movement. These parameters are directly measured from the 3 sensors that the company has installed on the ring. As this metric is OURA specific so we do not have actual data to compare its accuracy with, but in comparing the accuracy of the other parameters that the ring manufacturer uses for calculating this parameter, we found that RHR and HRV are 99.6% and 98% accurate. [33] (Approved)
- **Temperature:** This parameter is measured by a SE sensor that is installed inside the KTH lil buildings, and according to SE, all their sensors provide accurate measurements up to ± 0.2 degrees. So the temperature is considered accurate. [34]
- **Activity:** There is no defined measure for the activity to assess whether it's accurate or not, however the approach that OURA uses is to take data from the 3D accelerometer which seems a common approach to measure activity. This sensor is considered a reliable tool for measuring different activity related parameters, and that is because it delivers accurate results [35]
- **Readiness:** This parameter measures how well your overall health is, and how prepared you are for the day following. OURA also calculates the readiness of a person based on data from the sensors like the RHR and HRV so as proven before, since those parameters are accurate enough we can also consider the readiness to be accurate enough for this project. [36]

- Humidity: This parameter follows the same approach as the temperature. And according to SE, the humidity sensors are accurate up to +2%/-2% in the ranges from 0-80 % relative humidity measurements. So the humidity is considered accurate. [34]
- Restfulness: It is a measure of how soundly you slept through the night. Wake-ups, excessive movement and getting up from bed during the night will all take away from your overall restfulness. However, in this simple definition of restfulness, we can not approve this parameter since any small hand move, in-bed rotation can decrease this score and thus give a misleading result. [37]
- Sleep Latency: This parameter is defined to be the amount of time it took a person to fall asleep after they went to bed, according to OURA the optimal time for a person to fall asleep is 10 - 20 minutes, if a person falls asleep in less than 5 minutes, this can indicate that the person is over tired and if the person struggles to sleep within 20 minutes indicates that this person is having some anxiety. However, OURA does not provide any information about the accuracy of this parameter, so it is not assessed. NA
- Total Burn: this parameter refers to the total number of calories burned throughout the day, OURA does not provide enough information about the accuracy of this parameter, but they claim it to be accurate enough, or slightly bounced if the person did not wear the ring when exercising. In an experiment that was done to compare different wearables, OURA was the most consistent wearable device in the activity measuring. So this parameter is also approved. [38]
- Total Sleep Time: Oura analyzes your sleep by measuring the dynamics of your resting heart rate, body temperature, movement. Again we cannot determine the accuracy of sleep time since we have no access to the algorithm, and we think that there weren't actual tests done to test the accuracy of the algorithm. [11]

Objectivity: Since all the collected data is from the sensors of the OURA Ring, we can safely assume that it's completely unbiased, impartial, and unprejudiced, since it is qualitative data. (Approved) [39]

Reputation: The source of the data is from the ring, which means our only source is considered "trustworthy". Also, we are aware that the data was never modified, edited or manipulated, also the data is used by OURA to monitor sleep patterns for users, so OURA can not manipulate the data or they will risk losing their clients. All of this ensures that our data holds a good reputation and thus we approve this dimension. [40]

Relevancy: The data set we received from OURA contains 55 entries for each day, and in our modelling process, we are using 10 parameters, which are 8 from OURA and 2 from SE, this means that the dataset we have is covering 100 % of our needs. Thus, this dimension is approved.

Timeliness: Time is not an important factor in our project, in fact we have data ranging from multiple months (May 2020, December 2020, February 2021, MArch 2021). So we have a wide range of the year covered by the dataset, we also have samples from winter/summer times which ensures that the program is trained on different patterns. Also this project was done from January 2021 to May 2021 so the data is considered up-to-date. Thus the timeliness dimension is approved.

Completeness: The data from OURA has some missing entries, those can be owed the user forgetting to charge their ring, or due to contactless moments between the wearer's finger and the ring. However, we removed the days that contain the missing entries from our training sample so it doesn't affect the

model. The data from SE was 100 % complete. In summary, the data we used in the training and testing is 100 % complete, and this dimension is also approved.

Appropriate amount of data: there is no specific rule for deciding the sample size when training artificial neural networks (ANN), however there are some theoretical calculations and assumptions that help deciding the appropriate amount of data needed for the desired ANN. It is alluded to that the more parameters the network consumes, the more data it will need. Also there is a well known dimension that is often used for deciding the complexity of the learning model, in our case an ANN, this dimension is the Vapnik–Chervonenkis (VC dimension). The most significant outcomes in this regard are that the discrepancy between training and generalisation error is bounded from above by a quantity that grows as the model's VC dimension grows, and shrinks as the number of training examples increases.[41] But the difficulty in quantifying the VC dimension has led to hardly any application in practice. Therefore, scientists and practitioners tend to use a dominant rule which can be summarized in the following:

1. The VC dimension of ANNs is approximately the same as the number of weights. [42]
2. The sample size required to train the ANN is roughly 10 times the VC dimension. [43]

In summary, the amount of data that is appropriate and meaningful for training the model is approximately 10 times the number of weights. For calculating the number of weights (NW), we used the following formula:

$$NW = (I + 1) * H1 + (H1 + 1) * H2 + (H2 + 1) * O$$

I = Number of inputs (Parameters)

H_i = Number of neurons in Hidden layer number i

O = Number of outputs.

$$(9 + 1) * 8 + (8 + 1) * 8 + (8 + 1) * 1 = 161$$

This simple calculations suggests that the appropriate amount of data we need is $161 * 10 = 1610$ days. Unfortunately the number of complete days we have managed to collect from the dataset we received is 141 days. So we can not approve this dimension.

Interpretability: This dimension is not hard to assess, both OURA and SE provide well formatted definitions for the data they provide, also both companies provide numerical values for the different parameters. Most of the OURA values are, however, scores ranging from 0-100 but they also include the number of seconds for the total time and degrees of deviation in Skin temperature. In terms of SE, the same applies, they provide percentages ranging from 0 -100 for the relative humidity, and degrees for temperature. This dimension is approved.

Understandability: Like the previous dimension, this one is also easy to assess. The data came to us in excel sheets, which means that the data is structured by days and values for each day, we received different data sets for each tenant and then combined them together in the project's database. This means that the data is understandable and thus this dimension is also approved.

Consistency representation: The data like mentioned earlier, is formatted into days and each day contains the values specific for that day. In terms of SE data, it was a bit different, that the data was divided into 24 entries per day, that is a value for each hour, so we had to go through each day and select the values for the time which the tenant went to sleep. This ensures that we selected the value that had the most effect on the sleep of the tenants. After we did this. So, we had the same structure for data from SE as the data from OURA, and this dimension is approved.

Concise representation: the data is compactly represented, and this dimension is approved.

Accessibility: the data is accessible to all parties that have the right to look at it and those who signed the agreement with the users. This dimension is approved.

Security: The data was shared with us through secure communication channels that belong to KTH, this means that no third parties were involved. The data is also stored offline in our laptops and thus no cloud services are used. This ensures both the security of the participants and the security of the data from being lost or corrupted. This dimension is approved.

The following table gives a brief summary on the TDQM results presented above.

Table 5.1: Summary of the data quality assessment results.

Dimension	Example values from the data set	Assessment
Believability	NA	Approved
Accuracy	1- Sleep Score 2- Temperature (SE) 3- Activity 4- Readiness 5- Humidity (SE) 6- Restfulness 7- Sleep Latency 8- Total Burn 9- Total sleep time	1- Approved 2- Approved 3- Approved 4- Approved 5- Approved 6- Rejected 7- NA 8- Approved 9- NA
Objectivity	NA	Approved
Reputation	NA	Approved
Relevancy	1- Sleep Score 2- Temperature (SE) 3- Activity 4- Readiness 5- Humidity (SE) 6- Restfulness 7- Sleep Latency 8- Total Burn 9- Total sleep time	Approved

Timeliness	01/05/2020 and 01/02/2021 - 30/04/2021	Approved
Completeness	Data is given on discontinuous periods starting from May 2020, and until April 2021.	NA
Appropriate amount of data	141 days.	Rejected
interpretability	Language: English Units: Provided Type: Float numbers	Approved
Understandability	Date: 01/05/2020 Sleep Score: 82	Approved
Consistency representation	- Date: 01/05/2020 Sleep Score: 82 - Date: 02/05/2020 Sleep Score: 77	Approved
Concise representation	Date Sleep score ... Recovery index score . .	Approved
Accessibility		Approved
Security		Approved

5.2 Further Analysis Results

Multiple boxplots were done to verify the effects of temperature and humidity on the quality of sleep as studied in the literature review (see chapter 2.5). Figure 5.2.1 shows a boxplot of sleep scores and relative humidity for each data sample. There are 3 tenants total; tenant 1 and 2 data are during May of 2020, while tenant 3 data is during February-April of 2021. These boxplots convey multiple information about the OURA's sleep scores at different relative humidities. First, It can be seen that almost all the sleep scores are situated around the same range of relative humidity. That is due to KTH LiL controlling the relative humidity of their apartments to keep them around the ideal range for built environment. Second, the interquartile ranges (lengths of boxes) are longer at higher sleep scores (≥ 70) than they are at lower scores. This means that the high sleep scores are more dispersed around ideal ranges of humidity than low scores.

Figure 5.2.2 shows a boxplot of sleep scores and temperature for each data sample. These boxplots show similar results to the previous figure. All sleep scores are situated around the same range of temperature values, with higher sleep scores (≥ 70) having larger interquartile ranges than lower scores. This, as before, means that higher sleep scores are more dispersed around ideal ranges of temperature than low scores. The dispersion of OURA's sleep scores in the two figures agree with the studies in the literature review (see chapter 2.5) about the ideal range of humidity and temperature for a better quality of sleep. However, they also show that even within those ideal ranges, a large amount of sleep scores are still low.

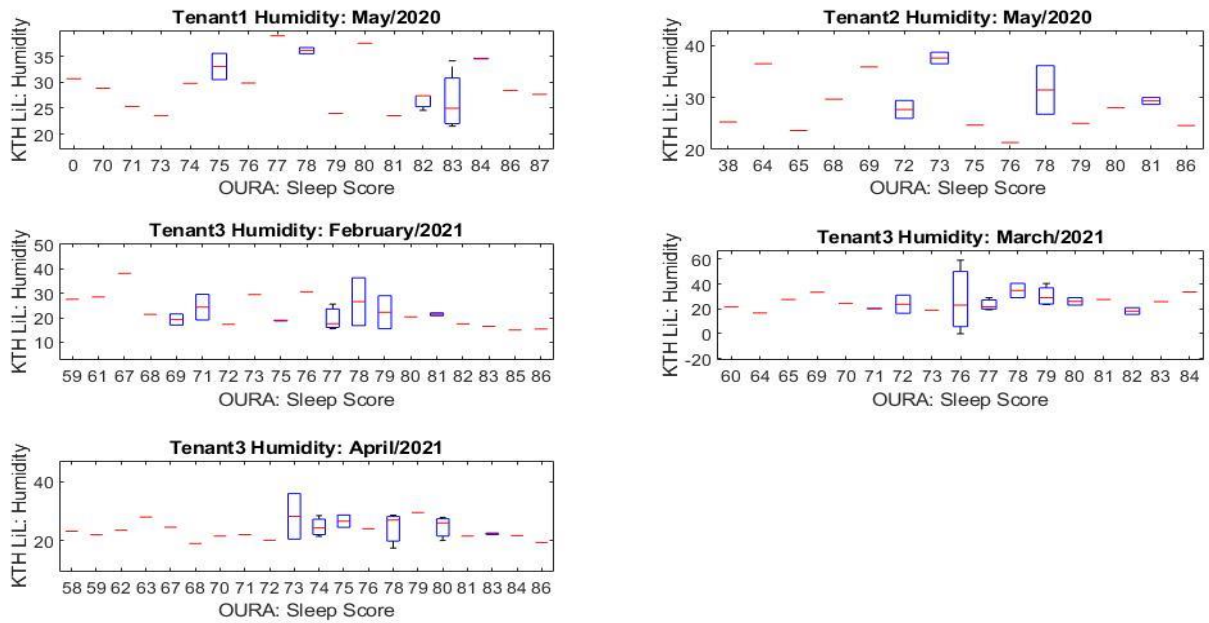


Figure 5.2.1: Sleep score vs Relative humidity

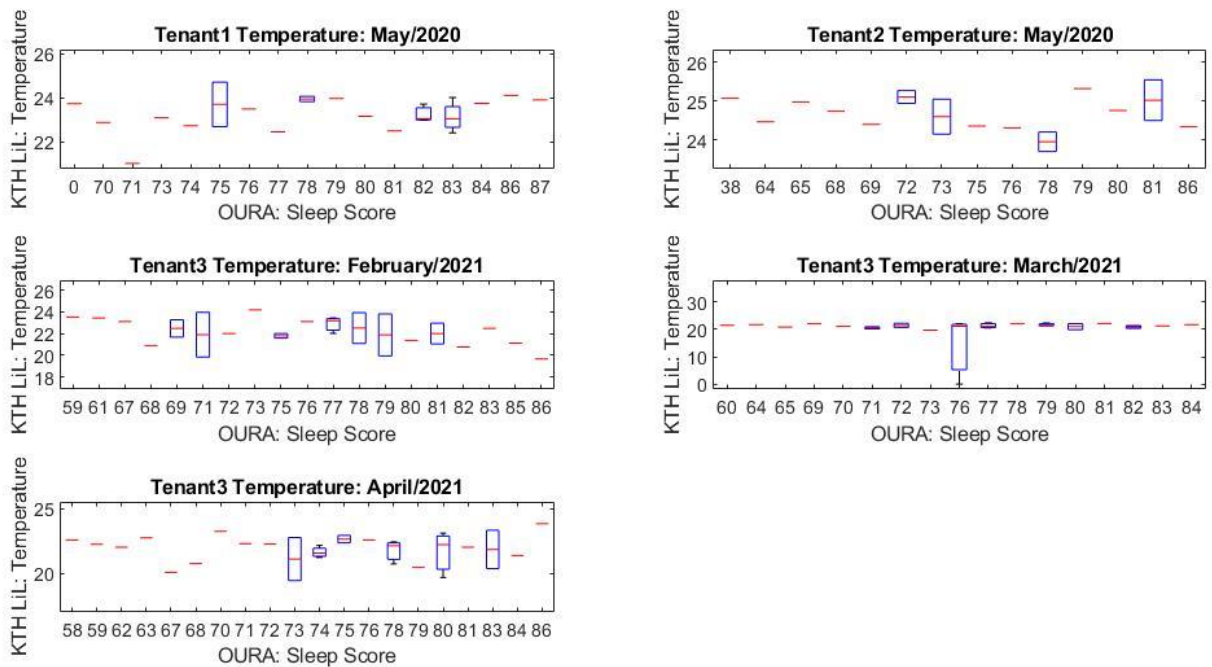


Figure 5.2.2: Sleep score vs temperature (°C)

5.3 Modelling Results

The collected 141 training data represent the time periods of: 01-05-2020 and 01-02-2021 to 30-04-2021. Each day holds physiological and built environment values for one of the tenants, as described in sections 3.3.1 and 4.1.

Figure 5.3.1 shows the results of training (fit) the model described in 4.3 with the training data. The figure specifically shows the training loss and the validation loss of the training data and validation data, respectively, over 150 epochs. These two losses are the values of the loss functions, described in 4.3, over the training data and the validation data that our model is trying to minimize. It can be seen that both losses start decreasing exponentially during the first <10 epochs. Then, they decrease slowly and steadily, converging at ~2.00-3.00. Both losses at 50 epochs are at ~4.00-5.00, and, at 150 epochs, they are at ~1.90-2.50. Even though that difference is very small, running the training over 150 epochs has still managed to reduce the training and validation losses by almost half of their values at 50 epochs. Having both losses converge ~2.00-3.00, instead of the ideal 0.00, could lead to some issues regarding accuracy of predictions. Ideally, both losses should be converging around 0.00.

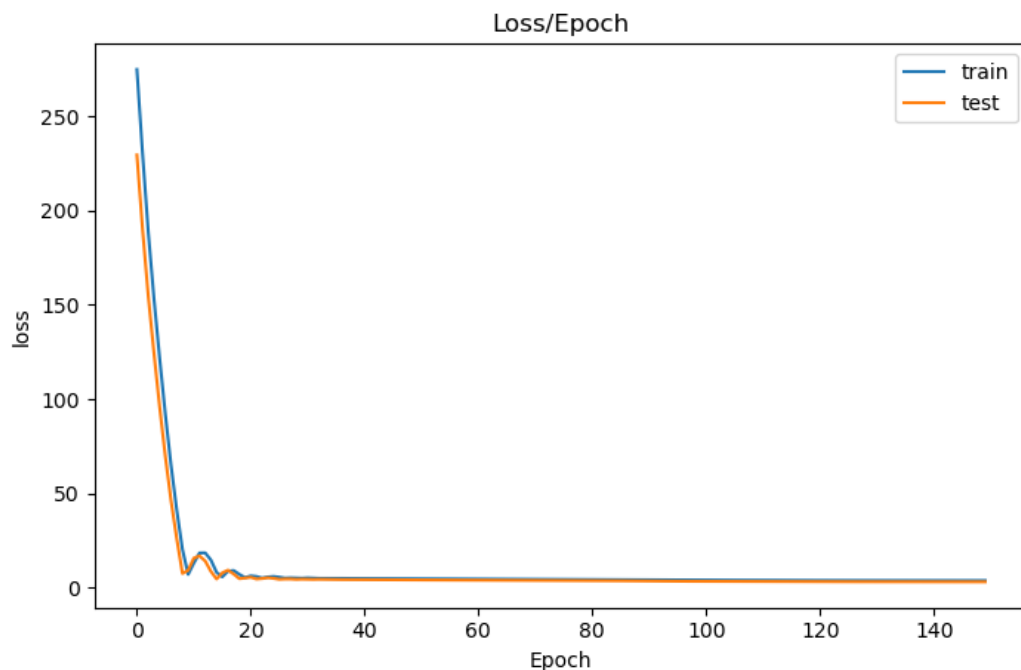


Figure 5.3.1: Loss/Epoch results

Furthermore, it was important to test how well the model could predict the sleep scores. In order to do so, and since our dataset is relatively small, we split the dataset into two sets: training set and testing set. The testing set consisted of 30 days worth of data, and the training set consisted of the rest. Training the model over the training set then predicting the testing set's sleep scores gave us 30 days worth of results (predictions). Comparisons between the actual sleep scores and the predicted scores are shown in Figure 5.3.2. It can be seen from the figure that the predicted values are close to the actual values, which presents the relationship between the sleep score and the environmental and physiological parameters. It can also be seen that those parameters can be used to model the sleep score by introducing a Multilayer Perceptron.

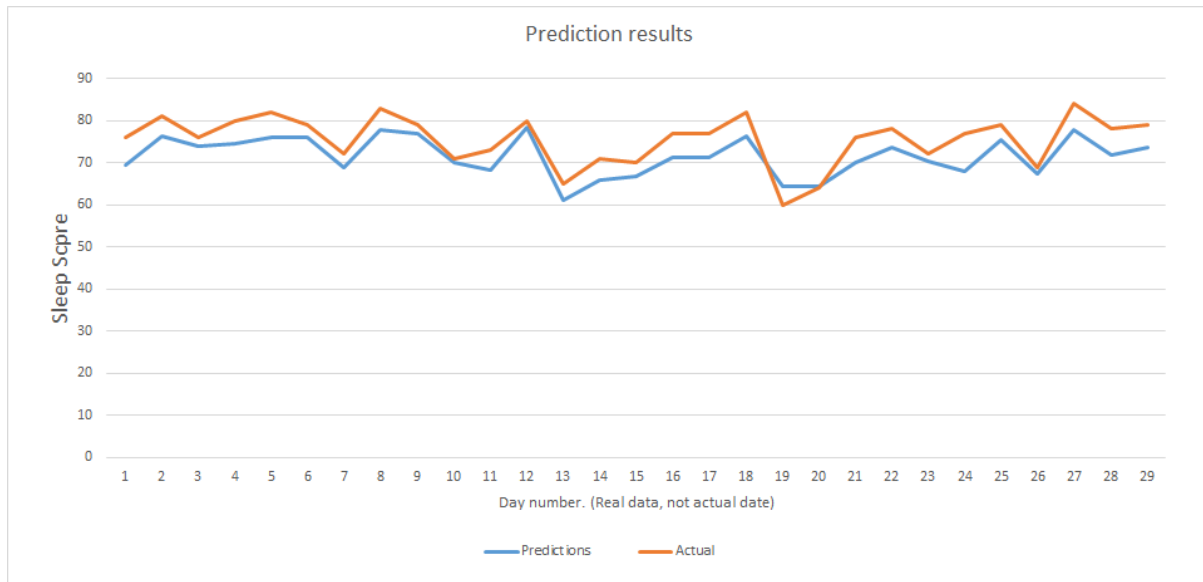


Figure 5.3.2: Predicted/Actual sleep scores

5.4 Discussion

Smart buildings are a significant application of IoT. These types of buildings use IoT devices to integrate the various complex units and IT systems that form the whole building. The integration allows the systems and units to communicate over a shared network. This communication and the ability to react to massive amounts of collected data by AI methods and other algorithms provide a better use of the building's resources. That means, for example, better energy efficiency, lower maintenance costs, and better security. Smart buildings have existed for a while, and there's an interest in seeing how far the advantages of smart buildings can reach. That's where KTH LiL, with its testbeds, comes into play.

Moreover, wearable devices have emerged recently as a new application of IoT. OURA ring is a wearable device that explicitly tracks sleep patterns, qualities, and other sleep-related information. One of the problems with wearable devices, including the OURA ring, is how reliable and accurate their information is. KTH LiL needed to use the OURA ring to understand the tenants better to test different scenarios and provide the ideal conditions for its tenants. However, in order to do so, extensive quality assurance needed to be conducted on the ring.

To begin with, we would mention that the results of the data quality assessment were satisfying. The results indicated that the data is applicable in this and similar scenarios. Our study assessed different dimensions (mentioned in 4.2) on different parameters. The results directly addressed which dimension is accepted and which is not.

Believability: this dimension was approved. Sensors measure the data entirely. Therefore, the values we have for each parameter are realistic and plausible. For example, in a period of 30 days, the total sleep time of one of the participants has ranged from 20000 to 28000 seconds, which is from 5.5 to 8 hours of daily sleep, and this is compatible with the results of a study that was done by university of Georgia. The study results reveal that, on average, university students get 6 - 6.9 hours of daily sleep. [44]

Accuracy: when assessing the accuracy of the data, we had to consider the accuracy of different parameters since each of the parameters is measured using different sensors and calculated using different methods. In table 5.2, we are presenting more concrete results from our assessment on each dimension. Out of 10 total parameters, we had five approved, one rejected, and four parameters that we could not assess their accuracy with the bit of information we have. The first parameter is the sleep score, and this parameter, in particular, is the most important one in our study as it measures whether the tenants are having a good quality sleep. Since this parameter is OURA specific, we could not compare our data to other data sets. However, having an accurate sleep score helps the model identify the tiny details that could affect the tenant's wellbeing and sleep quality. Then we have the ambient temperature; this parameter was also shown to be accurate. The more accurate measurement of the temperature we have, the better control we can get on the surrounding atmosphere, and thus the better results we can achieve. The activity was also one of the parameters that we could prove to be accurate. It is also a critical parameter since it determines how active a tenant was and how much rest they need. That plays a measure role in determining the predicted sleep score in a single day or the recommended amount of sleep for the following night. Readiness provides a score of how well or prepared a tenant is for the next day. That is also a score that is very important to be as high as possible. For example, having a readiness score between 85 - 90 indicates that this person is ready and rested for the day and thus needs the regular amount of sleep, but having a low score like 60 - 65 indicates that the tenant needs extra hours of sleep to rest fully. The humidity indicator is also critical to be accurate in terms of this study. Like the TA, it is one of the controllers that the model will adjust to increase the sleep quality. Restfulness, as much as this is a critical parameter that we need to get into our model, we could not find any information or enough knowledge on this parameter that supports its accuracy. Since the OURA ring uses interpretations from the 3D accelerometer to indicate wakeups and movement during sleep, any hand move or in-bed rotation can be interpreted as a wakeup and decreases restfulness. Thus we decided to reject its accuracy, this does not mean that we will not use it in our model, but for future consideration, this can be considered. Sleep latency, it is crucial for this parameter to be accurate enough. By having an accurate sleep latency score, the model will tell whether this person is overtired or anxious from the day before, so this can lead to a more accurate estimation of the sleep score. So the inaccuracy of the sleep latency score can be one factor that the prediction results weren't as accurate as of the actual values. Total burn, also like sleep latency, tells much information about the previous day's situation. We approved this parameter's information based on a comparison done with other wearables that measure a similar value, but having the ability to test its accuracy would increase the model's overall accuracy. Finally, the total sleep time is one of the most critical parameters in this model. The results have shown that the model recognizes a linear relationship between the total sleep time and the predicted sleep score. Hence, the model gave higher scores for the longest sleep time. That is true in some sense and is compatible with other findings in the literature review and the online search. Furthermore, it is reasonable as the tenants are sleeping more when they are relaxed and having a good sleep. However, it would be interesting to see how the model reacts to extreme sleep durations, which, unfortunately, we do not.

Objectivity: this is important to be approved since we do not want any data to be biased or modified to get actual results. Sensors measure the data we are dealing with, and we have no qualitative data.

Reputation: despite that we approved this dimension, but in fact that this is not much of an important dimension for our study, the reputation of the data is not as important to us as the accuracy and the objectivity of the data. Our study is subjective to the OURA ring and SE sensors, and this ensures that all the data are considered from good reputation sources.

Relevancy: when assessing the relevancy, many factors were taken into consideration, like how well this data is suitable for our study, whether we have all the data we might need or not. The

assessment came as an answer to these questions. Since the study is directed to the use of the OURA ring, the data is relevant to the study, and we had all the data we needed, except not in enough amount. Although the dataset contains more data than we used, we used only 19% of the overall data we received.

All other dimensions were approved, but since they did not affect the results, we are excluding them from the discussion. This ends the discussion in terms of data quality assessment.

Through TDQM, we realized that the OURA ring is in fact an appropriate tool to evaluate sleep quality. However, the study of sleep is a challenging study because it is hugely affected by psychological factors. That causes an issue of sleep scores affected by other factors beyond the scope of this study. Sleep score from the OURA ring is found from many physiological values. Some of these values can be affected by psychological factors or other factors related to a specific activity. For example, the restfulness value is easily negatively affected by anxiety, stress, alcohol consumption, and sleep apnea. Since the restfulness value contributes to 0.15 of the sleep score's value, the overall sleep score will also be negatively affected. A few other values are affected by similar and other factors, making sleep quality a challenging property to measure passively. That is why "traditional" methods, like polysomnography, are better at studying sleep. And, that's why medical centers still use the "traditional" methods over wearable devices to diagnose sleep disorders. Nevertheless, for our study, this issue can be seen in days with ideal ranges of temperature and humidity that should've contributed to getting high sleep scores, but they ended up having low sleep scores. This issue can be seen in figures 5.2.1 and 5.2.2. In order to mitigate this issue, a monitored study of tenants wearing the Oura ring in their building environment needs to be conducted. Such a study would be able to keep track of sleep scores heavily affected by other factors, like psychological and activity-related, which would lead to a better understanding of the OURA ring, built environment, and sleep quality.

Nowadays, artificial intelligence methods are getting introduced to many new fields, and they are becoming part of our everyday lives. AI methods essentially use input information to study, learn and figure out how they can achieve a particular task. One of the essential prerequisites of using an AI method is that people must have a considerable amount of input information. The large input helps the method maximize its success rates of achieving the particular task. However, that is not always the case, as some tasks don't require large inputs to solve. These tasks just require an appropriate AI method with proper initializations, arguments, and training to achieve their tasks with some level of success rates. From our modelling results, we can see that we were able to solve our task of predicting sleep scores by using the Multilayer perceptron method. Even though we had an input of small size, we could still achieve a slightly low loss rate of ~2.00 by choosing the appropriate number of training epochs (150) and initialization methods. This loss rate correlates with slightly high success rates of accurately predicting the values of the sleep scores of tenants. In return, this suggests that the sleep scores (quality of sleep), calculated from the OURA ring by tracking tenants' physiological information during nighttime, ultimately depend on built environment values surrounding these tenants. The built environment values this research studied were temperature and humidity.

With that being said, if our dataset were larger (around 1000 entries), then the model could've reached loss rates of near 0.00, which is the ideal rate for these types of models. Getting a loss rate that is not in the ideal range (0.00) means that the predictions will not be very accurate. The predicted values are 5-10 points around the actual values, as seen in the prediction results. This difference between the actual/predicted values can be reasoned to many facts. We are aware that when training the model, we merged the data from different tenants, but this was not an efficient move as OURA considers personal information such as age and weight when calculating different parameters. So our model was blind to this information since we do not have access to them. However, because of the data shortage, we had to make this compromise.

6 Conclusions and Future work

To finalise the discussion section, we would like to re-mention our research questions. The first question's regarding exploring the possibilities and limitations of measuring sleep quality from built environments and the Oura ring. Based on the data passing 11 dimensions in TDQM results and the Oura ring's ability to capture the effects of humidity and temperature on sleep quality through its sleep scores, we can say that the Oura is an appropriate tool for measuring sleep quality passively. However, since measuring sleep quality is very reliant on people's feedback, further studies need to be conducted that take into account some sort of user feedback. The next question is regarding the possibility to use ANN for predicting sleep qualities for tenants. Based on the modelling loss and prediction results, we can say that multilayer perceptron is an appropriate ANN algorithm for predicting sleep qualities by using the ring's sleep scores. The final question investigate whether the ring and SE can be used to provide personalized instructions to increase users' sleep scores. Based on the modelling results, the MLP prediction model can be extended into a recommendation model. Such a model would give personalized instructions for users to increase their sleep scores.

The main purpose of this work was to use the data from wearable devices and smart buildings to improve well-being parameters such as sleep scores. The wearable device we used was the OURA ring which specializes in sleep monitoring. The smart buildings are the buildings from KTH LiL and the data from the SE sensors installed inside the building. The original purpose of this thesis was to evaluate PMV for tenants in KTH LiL. However, after conducting some data analysis, we realized it was inefficient to use the OURA ring for PMV modelling. Firstly, the ring only provides nighttime data, and it presents the data the following day. Secondly, there were multiple PMV-essential variables that the ring does not provide, including metabolism rate and clothing insulation levels. Thirdly, to verify a PMV model, direct access to tenants' thermal comfort feedback is required, which we did not have.

We built a database that we can use for this program. We built the database using MongoDB, and the resulting database was exactly as we desired. We were able to store the data in the way that best serves our needs. We also did a data quality assessment to test whether the quality of the data is good enough for our project. The results of our assessment came as satisfying as we wished. The data quality showed great potential for the project and safely proceeded to the modelling phase. For the modelling phase, we had to conduct a heavy literature review to get enough knowledge about the modelling. In order to do the modelling, we had to make some choices, such as the programming language and the AI algorithm that is the best fit for our project.

This project raises many concerns but also opens wide doors for future works. One of the biggest concerns is the integrity of the tenants and the people benefiting from it. In our case, we had our participants sign an agreement that gives us the right to use their data in this project's scope during an agreed-on period. Many of the data being collected is considered personal data, and thus it is sensitive to use. Another concern is that smart buildings are not yet widely available, and thus applying such programs is restricted to areas and places where smart buildings are available.

Nevertheless, the potentials that this project might have for future uses are incredible. The tenants will have a better sleep quality in their everyday life, and thus their productivity, effectiveness, and performance will increase. Applying similar approaches to improve other life parameters can be beneficial. Also, using this program, building owners will have an insight into the amount of necessary energy needed to be consumed to achieve a good sleep quality, which will prevent potential losses on

wasted energy, like avoid using the air conditioning heavily. Also, testing the same idea using different algorithms would be interesting to see which algorithm gives the best results.

This was an explorative study for evaluating sleep quality with a wearable device and built environments of temperature and humidity. Further studies need to be conducted on the effects of using the OURA ring and built environments on the quality of sleep. A study could be done by having multiple tenants use the ring for an extended period of time, providing around 100-200 days worth of data. The study should have the tenants in a semi-monitored environment where it can take feedback and notes from the tenants about any psychological issues or inconsistencies with the data. Moreover, the study could still use an artificial neural network method to predict future sleep scores and compare them with feedback from the tenants. Another study could be done by using the ring and built environment to recommend ways to increase one's quality of sleep. A recommendation model can be built based on the ANN prediction model, where the model would notice low sleep score values and investigate how one could increase them. Such a model could be based on the built environments of temperature, humidity, CO₂, ventilation, etc., and information from the ring, like, sleep timing and activity rates.

We would also suggest that if possible, having more data will discover any other details that we could not see and provide better results. Also, an essential factor is to have another source of data that one can compare. In our study, we were subjected to the data we get from OURA without having the possibility of comparing the scores and the different values with another data source. Moreover, it may be interesting to test the results in a real scenario. We did not have the potential to apply our program to a real-life scenario. However, it will be knowledgeable to apply it and collect feedback from the tenants whether the results are actual or not.

7 References

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