WEARABLES: A TOOL FOR INVESTIGATING FATIGUE IN THE MINING WORKFORCE

by

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STATEMENT OF THESIS APPROVAL

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ABSTRACT

Fatigue is as complex as it is understudied, and it is a constant research topic in the mining industry. This study explores the possibility of investigating fatigue via the use of off-shelf wearable devices with the aid of custom applications. The developed applications follow the IoT architecture and tries to assess fatigue in an operational environment.

The assessment of fatigue is done via the use of psychological theories. Considering that fatigue is a complex biological phenomenon, both qualitative and quantitative data is collected to assess it. The qualitative data is collected based on the Karolinska sleepines scale. The quantitative data on the other hand follows signal detection theory and psychomotor vigilance tasks. A custom application named Real Time Fatigue Management (RTFM) was built to execute the tests on a smartwatch. The custom application includes a client application and an application server that handles requests.

To assess the application and proposed architecture, a case study is conducted with the workforce of a site. The study focuses on collecting qualitative and quantitative data. An additional aspect that interests this study is the deployment strategy adopted for the IoT solution and organizational OHSMS practices and culture. 26 devices were set up and out of these data collection was successful on 13, which leads to a deployment ratio of 50%.

The collected data points towards a relation between reaction time and fatigue and evidences the variation on fatigue throughout shifts. It points towards the need of more inputs to better understand fatigue. Further research on the topic to include other research questions is recommended, the study could benefit from a larger dataset and population.

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CHAPTER 1

INTRODUCTION

The study of fatigue and its impact in the workforce is a topic of major interest in the mining industry and needs further investigation. It's a persistent problem throughout mine sites and the industry needs improved tools, management approaches, and understanding to properly control and manage its risks. Recent history and studies shows that the industry has advanced in understanding fatigue and its effects on the workforce, on the other hand, it still lacks effective ways of quantifying and measuring fatigue on mine sites (Bauerle et al., 2018; Butlewski et al., 2015).

To help companies develop a better understanding of workforce fatigue, and how to measure it, this research focuses on developing a solution that collects worker's qualitative and quantitative fatigue related data. The data collection is based on psychology studies and focuses on utilizing the Karolinska sleepines scale (KSS), signal detection theory, and a psychomotor vigilance test (PVT) to quantify sleepiness and reaction times respectively (Basner et al., 2011; Miley et al., 2016).

To develop a solution that proves efficient and is able to collect data successfully, we decided to utilize Internet of Things (IoT) as our main technology since IoT applications have seen a growth in multiple industries in recent years (Gao et al., 2019; U.Farooq et al., 2015; Young & Rogers, 2019). Although the mining industry is not at the vanguard of technological advancements, occasionally showing resistance towards it, there are several applications of IoT to the mining industry (Bartos, 2007; Dehran, 2018;

Gao et al., 2019). As an example of IoT benefits, Dessureault (2019) demonstrates personnel and equipment management through IoT and its possible advantages to the mining industry.

1.1 Problem Statement

Butlewski et al. (2015) states that fatigue and its accompanying psychomotor and mental effects are factors that influences accidents on workplace. Since companies, regulators, stakeholder, and other parties involved are continually looking to improve safety in the workplace, one can say that there is the need to better understand and control miners' fatigue (Chen & Zorigt, 2013). Considering the very nature of mining operations, shift workers are expected to execute tasks that have a potential to generate injuries or accidents (Theron & Van Heerden, 2011). It's known that shift workers may experience more fatigue due to alterations in their circadian cycles, which once again suggests the importance of monitoring and understanding fatigue (Dall'Ora et al., 2016; Flynn-Evans et al., 2018; Mabbott & Lloyd, 2005).

Several approaches exist on how to manage fatigue, but researchers agree that a golden standard is still missing, and more research is necessary. As tools to help the industry in the search of improving fatigue management and prediction, several technologies were developed in recent years, such as: eye tracking technologies, cognitive tests, camera based systems, and other (Drews et al., 2020). There is enough evidence to support the belief that Internet of Things (IoT) can be a viable solution to explore the effect of fatigue on the workforce. This study is particularly interested in investigating how to better use wearables to achieve that end.

To achieve our end goal, we decided to utilize off the shelf wearable devices because these are easy to acquire and have a variety of sensors and technologies that interest us. Other than that, custom solutions are associated with limitations such as their traditional cost, development time, the lack of skills, and knowledge of the workforce to apply them (Young & Rogers, 2019). Nonetheless, there is a need to develop a framework that can be applicable to companies that wish to overcome technical difficulties (Gruenhagen & Parker, 2020). To guarantee that the workforce has the necessary knowledge to utilize the technology, a variety of support materials was developed, and the workforce went through training sessions.

1.2 Significance

Having input from the workforce as they operate throughout the day can provide key information for health and safety plans (Williamson et al., 2011). The safety culture of the company can also be impacted and changed if better indicators are achieved and continually measured (Stemn et al., 2019).

Ultimately the reason that motivates the constant research on the mining workforce fatigue is the fact that most studies are from other industries and that once better understood, operations can be safer. This study does not intend to present a new golden standard for fatigue monitoring, but it plans on showing the problems that the mining industry face and how technology can help to better understand them. It also plans to provide a tool that can be implemented in an existing OHSMS system and that provides incremental improvements to mine sites.

1.3 Research Objectives

Finally, the scope of this research focuses on surface mine operations due to connectivity limitations, and to the mines that are participating in the study. This choice has been taken because it simplifies some of the variables involved in the study and provides a good base for future studies. With it we intend to provide a case that shows that it is possible to have a better understanding of the workforce fatigue through the analysis of quantitative and qualitative data.

The proposed research is focused on surface mines that want to utilize better technologies and have more operational information, and a healthier and safer working environment. Therefore, this research main objectives are:

- Explore workforce fatigue and reaction time in surface mines.
- Develop a deployment strategy for IoT application in surface mines.
- Provide a case study for I and II
- Show how low-cost out of shelf IoT solutions can add value to mining operations.

To achieve what is proposed this study is organized as follow. First the literature review and any important background information is presented. The literature review is followed by the materials and methods used and developed for the study which leads to the proposed case study. During the case study, one explores how the materials and methods behave in a real mine site environment. Lastly, the collected data is analyzed through analytical processes and the case study is analyzed from a management and cultural standpoint.

CHAPTER 2

LITERATURE REVIEW

2.1 Health and Safety Management Considerations

The mining industry is a high-risk industry that can benefit from the implementation of Organizational Health and Safety Management Systems (OHSMS) (Chen & Zorigt, 2013). As safety practices improve throughout the globe less incidents, accident, and fatalities are expected each day and there are public expectations in making organizations safer. This reality exists within the mining industry and is a discussed topic with the general agreement that the industry needs to improve its safety in both organizational and individual levels (Tetzlaff et al., 2021).

OHSMS's definition is a delicate topic, on one hand it can be defined as a combination of elements in several levels that work together in an integrated way to improve health and safety performance. On the other hand, literature says that is a challenge to define OHSMS because it is not clear where to draw the line in deciding if a system should be included or not to as part of a OHSMS (Robson et al., 2007). For the purpose of this thesis its definition is: systems in general which can be defined as integrated and defined structures with inputs, processes and outputs—all emphasizing feedback to ensure the processes are working properly (CORE SAFETY, 2015).

Since the scope of OHSMS can be vast and encompass several aspects in an industrial scenario there is the necessity to narrow down the elements that constitute an OHSMS. Redinger & Levine (1998) and CORE SAFETY (2015) provide the core to narrow down OHSMS in areas and elements that can be targeted in order to improve safety in general operations and in mining operations respectively. Table 2.1 shows a variety of elements that are part of an OSHMS system and that are important when analyzing these systems.

Even though the table shows elements from two different sources and with different focus it is interesting to note that there are overlaps to each other. One could say that the 3 major areas in the proposed elements are management, people, and workplace as shown in Figure 2.1 which align with what is proposed by WorkSafeBC (2021).

Even though some of the proposed elements are out of the scope of this research understanding what composes a OHSMS provides valuable information to decide which elements are a target of interest. Another interesting take on these elements is that they support the necessity to target both individual and organizations to achieve a safer and healthier working environment.

Considering that several elements come from individuals, and that these elements are related to human behavior, it is necessary to understand what drives and affects them. Some factors that play a role in employee's behavior are knowledge, expectations, attention, goals, health, fatigue, age, culture, culture, stress, and other. Behavior affects safety and an example of it is the Chinese coal industry in which human factors account for 80%-90% of accidents which tend to be caused by fatigue, emotional instability, rebellious attitudes due to bad management, and even boredom generated by tasks. (Liu & Luo, 2012).

Table 2.2 provides guidance on organizations and employees responsibilities to make a safer working environment. Since organizations and management play an important role in making an operation safe, they should question on how to improve health and safety standards. This question leads to several different answers and possibilities but considering the employer responsibilities presented on Table 2.2 the general take is that management should always try to educate, identify, assess, and control health and safety standards. Haas & Yorio (2016) propose the need to evaluate OHSMS's based both on objective and subjective measurements and advocate those psychological perceptions should play a role in those systems. Considering how complicate an OHSMS can become, literature supports (Theron & Van Heerden, 2011) investigating fatigue to diminish the number of fatalities and that having a better understanding on how OHSMS's can help managing it could prove vital.

2.2 Fatigue

Fatigue is as complex as it is understudied (Bauerle et al., 2018), especially in the mining industry, and it has been a topic of constant interest to organizations such as the National Institute for Health and Safety (NIOSH). To better understand what fatigue is, its causes, and implications to the mining industry, its necessary to review it and learn from other industries.

2.2.1 What is fatigue?

Formally defining what fatigue is has proven to be a difficult task due to its complex nature and number of behavioral and psychosocial processes it involves (Shen et al., 2006). Due to its nature, it's hard to define it with certainty but a common agreement is that it is a biological phenomenon (Fletcher et al., 2015).

Two definitions are of value for this study. The first, from Caldwell et al. (2019) which considers fatigue as the state of feeling very tired, weary or sleepy resulting from insufficient sleep, prolonged mental or physical work, or extended periods of stress or anxiety. The second is the three-factor conceptualization that Frone & Tidwell (2015) propose which is one of the most referenced by researchers (Bauerle et al., 2018).

The general term work fatigue represents extreme tiredness and reduced functional capacity that is experienced during and at the end of the workday. Work fatigue divides into physical, mental, and emotional. Each of these subcategories reduce workers capacities to engage into activities that demands the relative capacity and presents itself as its relative tiredness (i.e., a worker experiencing physical fatigue would feel physically tired and would avoid engaging in physical demanding activities) (Frone & Tidwell, 2015).

2.2.2 What causes fatigue?

Several studies provide insight and understanding on what causes fatigue. One of such studies divides the origin of fatigue in lack of sleep and/or from long work hours (LWH) and boredom (Caldwell et al., 2019). Other sources take different approaches when identifying fatigue.

A categorization of particular interest divides the causes of fatigue in individual-based causes and work-based causes (Williamson & Friswell, 2013). This categorization is of particular interest because it shows that organizations and workers are responsible for fatigue management and until both acts, it will continue to happen. In terms of organizations, some of the contributors to fatigue are: time on shift, number of breaks, shift type, shift pattern, total work time and recovery, and type of work (Williamson & Friswell, 2013). When it comes to the individual level, pre-existing medical conditions, and age-related changes are some of the major contributors (Williamson & Friswell, 2013).

Finally, another classification of contributors to fatigue divides them into: general, mental, and muscular (Techera et al., 2016) which relates to the definition of fatigue proposed by Frone & Tidwell (2015). Table 2.3 summarizes Techera et al. (2016) findings and definitions to fatigue contributors. Considering mining operations nature, contributors such as shiftwork, LWH, repetitive work, and others, relates to the industry and tend to cause fatigue on operators; Therefore, it is clear that the mining industry has factors that influences fatigue and it needs to better understand it in order to improve its management. Mabbott & Lloyd (2005) shows how important it is to explore and understand some of the variables related to fatigue in the mining industry and what are its influences on organizations.

2.2.3 Effects of fatigue

After defining what is and what causes fatigue, one fundamental question is still missing: what are the effects of fatigue? Ultimately, its effects are what makes studying and understanding fatigue so important, especially in mining. A common understanding is that fatigue is considered a threat and could lead to accidents and incidents in an industrial environment. Organizations dedicate themselves to better controlling it because it affects not only individuals, but organizations.

Individually, there are several effects associated with fatigue, such as (Caldwell et al., 2019):

- Reduced decision-making ability.
- Reduced ability to do complex planning.
- Reduced communication skills.
- Reduced productivity or performance.
- Reduced attention and vigilance.
- Reduced ability to handle stress on the job.
- Increased reaction time –in speed and thought.
- Loss of memory or the ability to recall details.
- Failure to respond to changes in surroundings or information provided.
- Inability to stay awake (e.g. falling asleep while operating machinery or driving vehicles).
- Increased tendency for risk-taking.

- Increased forgetfulness.
- Increased errors in judgement.

Drews et al. (2020) provides a case study that explores the effect of fatigue in a mining environment. Among his findings, he reports some of the effects of fatigue and shows how important operators' awareness to fatigue is. Lastly, it is shown how experience affects employee's awareness of fatigue and how important it is to understand it.

Finally, Dawson & McCulloch (2005) explores how fatigue relates to incidents and present what they call an error trajectory, which shows several layers that leads to an incident. It is important to understand the presented layers in order to prevent fatigue related incidents from happening. An important aspect of fatigue and incidents is that they relate most industries and tend to follow the same error trajectory 5 levels error trajectory presented by Dawson & McCulloch (2005).

2.2.4 Fatigue monitoring technologies

Recent history has seen a growth in number of fatigue monitoring technologies. Each of these tries to address fatigue via a different combination of sensors, measurements, and techniques, and each of them have been successful to a certain extent (Caldwell et al., 2019). Among those technologies there is a variety of solutions such as: cognitive tests, monitoring via wearables, EEG caps, camera based systems, pupillometry, fitness for duty tests, and other (Choi et al., 2018; Dawson et al., 2014; Drews et al., 2020; Mabbott & Lloyd, 2005).

Even though several technologies have been developed, there is a necessity to investigate fatigue by not considering it simply as a technical and measurement issue, which shows possibilities for different studies (Aaronson et al., 1999; Drews et al., 2020). Most tools utilize sensors data and tend to not consider individuals subjectiveness; Therefore, considering the nature of fatigue, there's value to the individual subjectivity and this should be considered as a possible input for modelling and/or assessing fatigue.

Another aspect of these technologies is how invasive they can be and their effectiveness. Drews et al. (2020) exemplifies in his study how technologies can have low acceptance and can be considered a distraction on operations. As an example, EEG caps and camera-based systems have faced resistance from operators due to feeling of “having their privacy invaded.”

One final problem that persists when analyzing fatigue monitoring technologies is their validation. Validating fatigue monitoring technologies continues to be a challenge even though better technologies keep being developed and health and safety standards improve (Hartley et al., 2000). Ultimately, it is a challenge to provide an optimal technological solution that is well accepted, provides good information, and is enforced throughout mining operations (Hartley et al., 2000). Having this on mind, any auxiliar development towards this optimal technological solution is of value.

2.3 Psychology Tests

Psychological tests play a vital role in assessing fatigue and are necessary to provide an approach towards investigating it. A number of tests and theories are used to investigate sleep and have been used in investigating fatigue, among these 3 seems appropriate to use in this study (Hursh et al., 2004; Van Dongen, 2004):

1. Signal detection theory (SDT).
2. Psychomotor vigilance tasks (PVT).
3. Karolinska sleepines scale (KSS).

SDT was first studied in the early 1950s in the context of World War II. Its first uses were in radar detection technologies and one can simplify it as being the theory that demonstrates the process of identifying a signal against a noise (Swets, 2001). Even though the theory first findings are 70 years old, not much has changed in terms of the mathematical models developed to evaluate it.

The theory is stable and has given major contributions to research that study human behavior and responses. Since SDT is applied when two different stimuli need to be distinguished (signal and noise), and that it has been utilized in several fields of science (Stanislaw & Todorov, 1999) it motivates us to see how it can relate to studying fatigue in the mining industry.

Other than SDT, PVT, and the KSS provide additional information to the study of fatigue. PVT is based on measuring reaction times of users and provide a numerical value that relates to user fatigue. On the other hand, KSS provides a categorical approach to analyzing sleep levels that are directly related to the study of fatigue.

2.3.1 Signal and noise

The base of SDT is signal and noise, the whole theory revolves around those two concepts; Therefore, it is important to clarify what each of them are and how they relate to the theory itself. To clarify it, consider an auditory experiment in which users are exposed to a light source and the listener needs to answer if it blinked green (yes) or if it blinked any other color (no) (Macmillan, 2001).

The presence of the expected color is considered the signal while any other colors are noise. Other sources are considered as being noise due to the presence of variability in sensory systems (Macmillan, 2001), and noise can also be defined as any stimulus not classified as signal (McNicol, 2005). As there is a constant change between signal and noise the observer will most likely mistake some of the signals for noise and vice-versa.

The fact that observers will mistake signal and noise leads to 4 different answer possibilities detailed below and summarized in Figure 2.2.

1. Hit: whenever the signal is present and identified.
2. Miss: whenever the signal is present but not identified.

3. False alarm: whenever the signal is not presented but identified.
4. Correct rejection: whenever the signal is not present and is not identified.

Both hit and correct rejections are the expected answers, on the other hand, misses and false alarms are incorrect answers. These categories are important for statistical analysis and better understanding of one's behavior (Wickens, 2001) and will be further explored in Chapter 2.

2.3.2 Yes/no tasks

There are a number of task options when utilizing SDT, we will focus on the yes/no task for two reasons: it represents some of the most classical examples and studies (Swets, 2001), and it adapts well to how we conduct our study. This type of task is similar to the example shown previously (see 2.3.1), for clarifying it we will focus on a visual example.

Considering a scenario that a visual stimulus is presented in a screen to an observer that keeps watching the screen. The stimulus can be composed of noise or signal+noise and the individual must detect when the signal appears. Now consider that the individual was exposed to 300 stimuli, 200 containing signal+noise, and 100 containing noise.

Previously, it was shown that it is important to divide results in 4 categories to better understand one's behavior, an example that shows why this is important is: what happens if a person answers 300 times that a signal was present? He would have a 100% hit rate, but that's not representative of what actually happened (McNicol, 2005); Therefore, only the number of hits is insufficient and there's the need to analyze the number of correct rejections to have a proper understanding of the test in its total. Considering

Table 2.4 that presents an example of raw data we can summarize it as probabilities in Table 2.5 following the notation shown below, and present in McNicol (2005).

(a) $P(x|s)$: that is, the probability that the evidence variable will take the value x given that signal was present.

(b) P(x|n): the probability that the evidence variable will take the value x given that only noise was present.

Hits and false alarms reflect two factors: response bias and degree of overlap between signal and noise. Response bias is the tendency to respond yes or no in the proposed task, while the overlap shows how much the noise is confused with the signal (Stanislaw & Todorov, 1999).

2.3.3 Psychomotor vigilance test (PVT)

The PVT is one of many tests developed to assess performance related to sleep loss, and it uses simple reaction time (RT) to visual or auditory stimuli that happen at random intervals (Basner et al., 2018; Basner & Dinges, 2011). This type of test is based on traditional stimulus-response tests and one of its main differences is that its repeated administration does not affect its results (Basner et al., 2018; Dorrian et al., 2004).

Its downside is that the traditional version lasts for 10 minutes turning it difficult to use environment where time is critical and there’s a constant push towards productivity. On the other hand, the brief psychomotor vigilance test (PVT-B) which lasts 3 minutes provides good evidence that the test duration can be reduced to achieve equilibrium between the test reliability and its operational feasibility (Basner et al., 2011; Basner & Rubinstein, 2011).

Basner et al. (2011) supports the test validity and shows that it is sensible to sleep deprivation leading to it being a potential indicator of fatigue (based on the definition proposed on 2.2). Nonetheless, it’s also shown that the results are meaningful in real world terms making PVT-B an ideal candidate for studying fatigue in mining operations (Basner & Rubinstein, 2011).

Another consideration that needs to be considered is the hardware and environment necessary for the test's execution. The tests are originally performed on the PVT-192 (Ambulatory Monitoring Inc., Ardsley, NY) a handheld device built specifically for the test considered as being its gold standard (Basner et al., 2011). Other studies such Matsangas & Shattuck (2018) explores the use of a wrist-worn device to execute the PVT test and support its use for short PVT test. Kay et al. (2013) verifies the possibility of using a touch screen to execute the test and concludes that it is feasible especially when the gesture that records the RT is to tap the screen with your finger. The cited sources show that even without the PVT-192 device, there are ways of executing a PVT test in a reliable and efficient manner.

Since the PVT measure reaction times, it is necessary to understand what the collected numbers mean and how they can be used to interpret the collected results. According to Dorrian et al. (2004) the key value to look for when conducting PVT tests is the reaction time threshold of 500ms which represents a possible lapse of attention

2.3.4 Karolinska sleepines scale (KSS)

To explore the subjectivity of sleep levels, we decided to utilize the KSS, it was first defined by Åkerstedt & Gillberg (1990) and it's used to define the subjective level of sleepiness on a certain time of the day. It indicates the level of sleepiness that a person feels in the last 10 minutes and it has been validated in other studies, especially shift work, jetlag, driving abilities and other (Shahid et al., 2012).

An interesting example of the effectiveness of the KSS is the study conducted by Kaida et al. (2006) that compares it to electroencephalogram results. Since the KSS measures subjective sleepiness, it is a self-reported measure following the 10-point scale presented in Table 2.6. We are highly interested in this scale because it has good correlation to EEG's and can provide non-invasive measurements which we believe that will help understand fatigue in mining environments.

2.4 Internet of Things (IoT)

To perform a PVT test based on SDT, a technological solution is necessary to help with real time assessments, collecting data while obeying health and safety policies, and guaranteeing data integrity. For that reason, IoT is explored as a possible solution since it can have a good acceptance and its use in fatigue monitoring has been limited thus far. This chapter focuses on detailing all the instruments and layers necessary when developing an IoT solution, and how it can help this study. It also brings a review on the technologies that are currently on use in the mining industry and why literature supports that IoT is a powerful ally to the mining industry.

2.4.1 Definition

IoT resumes itself on how things communicate to each other and to people; Therefore, it focuses on machine to people (M2P), and machine to machine (M2M), this technology keeps gaining space as industries turn more competitive and look to innovate their operations (Lee & Lee, 2015). According to Rayes & Salam (2019) in its simple form IoT is considered a network of physical elements empowered by sensors, identifiers, software, and internet connectivity.

Recent years have seen an increase in the number of devices connected to the internet as well as how we as humans interact with those devices and how each of those devices interact with each other (Rayes & Salam, 2019). The interaction between devices and/or machines has been a topic of research for years and its research has increased substantially in the last decade (U.Farooq et al., 2015). Since human beings are always on the move, an essential aspect that explains the increased use of IoT is its mobility and ability to answer specific needs swiftly (John Dian et al., 2020).

The use of IoT in industries is one of the focus of research that try to identify how IoT can improve operations, be it in terms of production, workflow, interactions, or safety

(Lee & Lee, 2015; Molaei et al., 2020). There is a vast realm of possibilities for IoT which includes wearable solutions due to their ease of use, unexplored capabilities, and capacity to substitute more traditional solutions such as smartphones and/or tablets for specific tasks in mining environments (Mardonova & Choi, 2018).

IoT-enabled wearable devices are worn devices that have the capacity to connect to the internet, send, collect, and receive data (John Dian et al., 2020). There is a vast number of out-of-shelf wearable devices available, and one of the most traditional solutions are smartwatches and fitness trackers. Smartwatches are computerized devices intended to be worn on the wrist, what makes them unique is their ability to carry different sensors that are constantly measuring variables such as: heartrate, activity, location, fitness/health tracking, and more recently oxygen levels (Mardonova & Choi, 2018). The variety of sensors available on smartwatches via custom applications enable the possibility of investigating fatigue through them.

2.4.2 Architecture

To provide a scalable solution IoT demands an infrastructure to be on place, and several layers generally composes this infrastructure (Berte, 2018). The previous section defines IoT as a technical solution with multiple layers that communicate between themselves, this section describers the main layers of an IoT solution in further detail. Whilst literature shows a variety of ways to break down IoT solutions (U.Farooq et al., 2015; Young & Rogers, 2019) the one thought to be the most appropriate for this research is described. Two essential concepts for IoT deployment are shown: IoT architecture, and client-server architecture.

2.4.2.1 Client-server architecture

Client-server architecture is the most general type of architecture utilized in software development and is used in almost everything that is somehow related to the internet. There are four basic concepts necessary to explain client-server architecture that are connected to each other: client, server, request, and response.

A Client/Server network is a type of network which consists of one higher performance system, the Server, and several mostly lower performance systems, the Clients. The Server is the central registering unit as well as the only provider of content and service. A Client only requests content or the execution of services, without sharing any of its own resources (Schollmeier, 2010).

Requests happens when the client sends a requisition to the server and expects to receive a response. Responses on the other hand, are what happens after the server receives a request, processes it, and replies the client with information in the form of data, response codes, text, and other (Oluwatosin, 2014).

Some of the advantages of utilizing a client-server architecture include modularization of the development, ease of troubleshooting problems, data security, better processing of information. A client-server architecture that is interesting and applicable to IoT is the 3-tier architecture which possesses a middleware between client and database. The middleware is also called application server and is responsible for pre-processing data and accessing an available database. Figure 2.3 details how requests and responses (results) happen in a 3-tier architecture. IBM Cloud Education (2020) resumes the 3-tier architecture into the following:

1. Presentation tier: user interface and communication layer of the application, where users interact with it.
2. Application tier: in this tier, information collected is processed following a set of business rules.

3. Data tier: is where the information processed by the application is store and managed.

2.4.2.2 IoT architecture

Madakam et al. (2015) provides an overview of different IoT architecture but the one that breaks it into: sensing layer, access layer, network layer, middleware layer, and application layer, which aligns with the client-server architecture seems to be the most appropriate one for this research. An adapted version of this architecture is considered for this research for two main reasons; First, it is applicable to the solution developed in this research, and second, there are other sources that support a similar architecture (Čolaković & Hadžialić, 2018; Lee & Lee, 2015).

Figure 2.4 Provides an overview of the basic architecture used on IoT development and deployment while showing basic responsibilities of each layer and how they can relate to the client-server architecture.

It is interesting to note that even the most basic IoT architecture still has 4 layers which add complexity to the deployment of such solutions but at the same time provide flexibility in the development phases and ease of maintenance.

The sensing or perception layer is responsible for gathering and collecting data from sensors. In this layer, the data is sent to the network layer that is responsible for transmitting it. The sensing layer is also responsible for identifying devices and/or users via an identifier and some of the challenges that if faces are processing capacities, memory management, connectivity, and battery capabilities (Čolaković & Hadžialić, 2018). In terms of client-server architectures this layer is the client layer.

The network layer is responsible for communicating with other devices and/or the middleware layer. It operates via the use of several technologies such as Wi-Fi, LTE, Bluetooth, 3G/4G, Zigbee, and other (Mahmoud et al., 2016). For this research, the focus is on the use of Wi-Fi technologies and 3G/4G because this is the infrastructure that tend to be available on mine sites.

Pre-processing data, filtering, and selecting are responsibilities of the middleware layer. Cloud computing is the most common type of middleware layer due to its scalability and deployment abilities provided by companies such as Azure and Amazon Web Services. This layer guarantees that only registered devices that follow a certain data structure have access to the database and it provides data security and integrity against several types of attacks (Čolaković & Hadžialić, 2018).

Finally, the application layer is the one that provides IoT with such a vast number of possibilities. This layer enables industries and researchers to develop a variety of custom applications that tries to answer specific needs, such as investigating fatigue (John Dian et al., 2020). This layer utilizes the available hardware and through custom code that communicates with the hardware access sensors and communicates with the network layer. There are a variety of Software Development Kits (SDK) available to develop custom applications and they use all sorts of coding languages such as: c, C++, C#, Java, JavaScript, and other (Čolaković & Hadžialić, 2018).

2.4.3 IoT in the mining industry

IoT has been used in the mining industry to investigate a number of possibilities related to health and safety even in underground mines which justifies the interest in exploring it (Jo & Khan, 2017; McNinch et al., 2019; Singh et al., 2018). IoT capabilities of monitoring, collecting, and transmitting data are promising towards the study of fatigue but the industry still lacks a uniform approach to deploying and developing custom IoT solutions.

In terms of wearables, which are the main interest of this research, there are a different number of applications and devices that can be used in the mining industry.

Table 2.7 shows applications developed for wrist wearable devices (Mardonova & Choi, 2018). The focus on wrist wearable devices comes from the lack of literature focusing on off the shelf solutions, most of the studies that explore fatigue utilize other types of wearable devices such as wearable cameras, smart eyewear, and EEG caps, making it an interesting research topic.

Smartwatches are the most interesting for this research due to the equilibrium between economic investment, sensors, out-of-shelf availability, and customization. Finally, it is noticed that more research needs to be done on the assessment of fatigue via IoT devices because most applications focus lies on equipment.

Another aspect that IoT brings with it is the necessity of having a workforce open to it, which at the moment the industry is still struggling to find (Molaei et al., 2020). A constant problem when dealing with this type of technology are trust issues, both from the workforce and management levels, even though there are a variety of examples on the use of IoT in the mining industry and how it can benefit from them. Table 2.7 shows examples of IoT applications and their expected outputs (Molaei et al., 2020). It is interesting to note that most traditional IoT applications focuses on equipment and monitoring conditions in the mine which supports the decision to research the use of IoT focusing on operators and people.

When focusing on wrist wearable devices, there are still a variety of fields that can be explored. Table 2.8 shows the summary of open research topics/applications of wrist wearable devices for the mining industry (Mardonova & Choi, 2018). Mardonova & Choi (2018) consider that smartwatches do not have health and safety capacities but most recent smartwatches act both as a traditional smartwatch and a fitness tracker; Therefore, smartwatches sum the capacities of fitness trackers to it.

2.4.4 Challenges and possibilities

Even though IoT has many possibilities it necessary to consider the challenges that come with those. One of the first challenges to arise when talking about IoT and the mining industry is the curriculum/expertise of the workforce. Even mining engineers, which tend to have the highest level of education in a mine lack formal education in IoT related topics such as application development, deployment, maintenance, data management, and monitoring (S. D. Dessureault, 2006). If that is true for mining engineers, one can imagine that it is also applicable for operators. Since operators constitute the majority of the workforce in a mine training them to utilize new technologies and how to deal with them is of essence (Molaei et al., 2020).

Among the challenges that IoT face, both Lee & Lee (2015) and Čolaković & Hadžialić (2018) present a series of points that are still hard to overcome and are synthetized in: data management, privacy, security, communication, standardization, and even architecture. When it comes to the mining industry, there are additional challenges that must be faced to implement IoT solutions that happen due to the dynamic nature of mining operations that are in constant change and networking capacities (Zhou et al., 2017). Lastly, in some cases there is a lack of knowledge about mining practices and culture by IoT providers which can difficult implementing successful solutions considering how unique and somewhat chaotic the mining industry is (S. D. Dessureault, 2006; Gackowiec & Podobińska-Staniec, 2019).

Even with the number of challenges associated with the successful implementation of IoT solutions its possibilities justify why research groups see it as one of the paths that the mining industry needs to follow (Deloitte, 2018; Zhou et al., 2017). Among the organizations that study and incentive studying health and safety technologies NIOSH keeps making efforts in IoT solutions and standard deployment techniques (Botti et al., 2015; Kumar & Tauseef, 2021).

Molaei et al. (2020) provides examples of the possibilities of IoT towards the mining industry such as predictable mining operation, mining safety increases, surveillance systems and optimization due to efficient data presentation. Other possibilities exists and their range in application goes from equipment optimization to employee condition and environment monitoring systems (Zhou et al., 2017).

A recent example that details the use of IoT in the mining industry and its capacities is the study proposed by S. Dessureault (2019). In his work Dessureault shows the advantages of exploring an IoT based approach which include operational, economical, and modern concepts such as gamification. A fact that is for sure is that IoT use in the mining industry is increasing but there are not many literature studies to consult on how to proper apply IoT to this industry (Aziz et al., 2020).

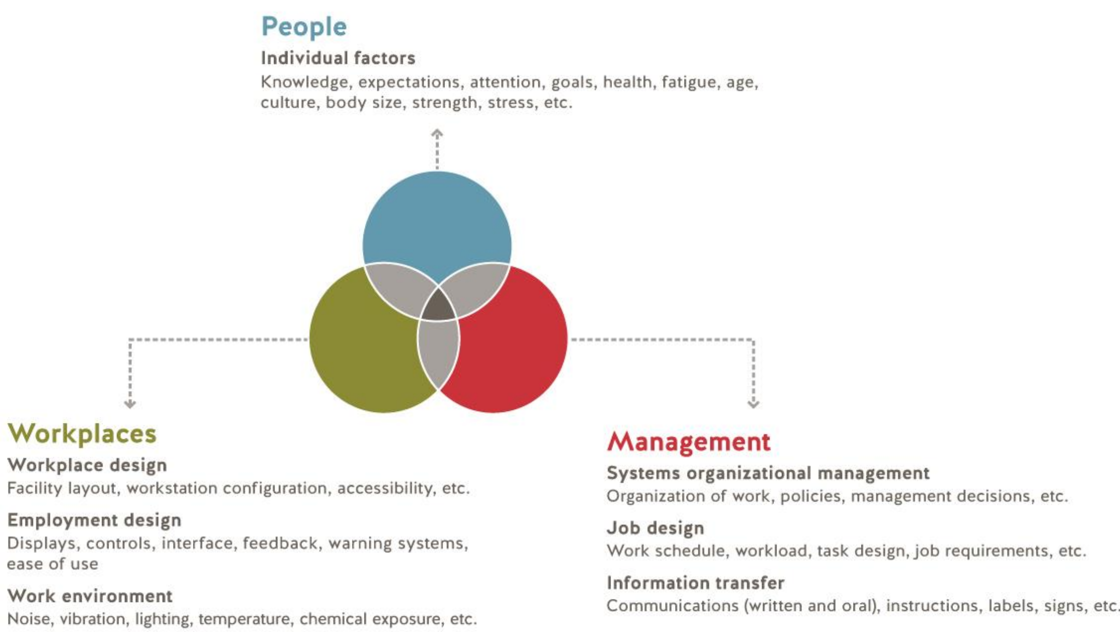

Figure 2.1 Interaction of human factors in organizations

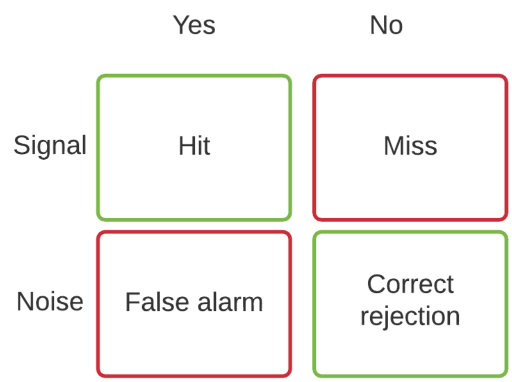

Figure 2.2 SDT answer classification

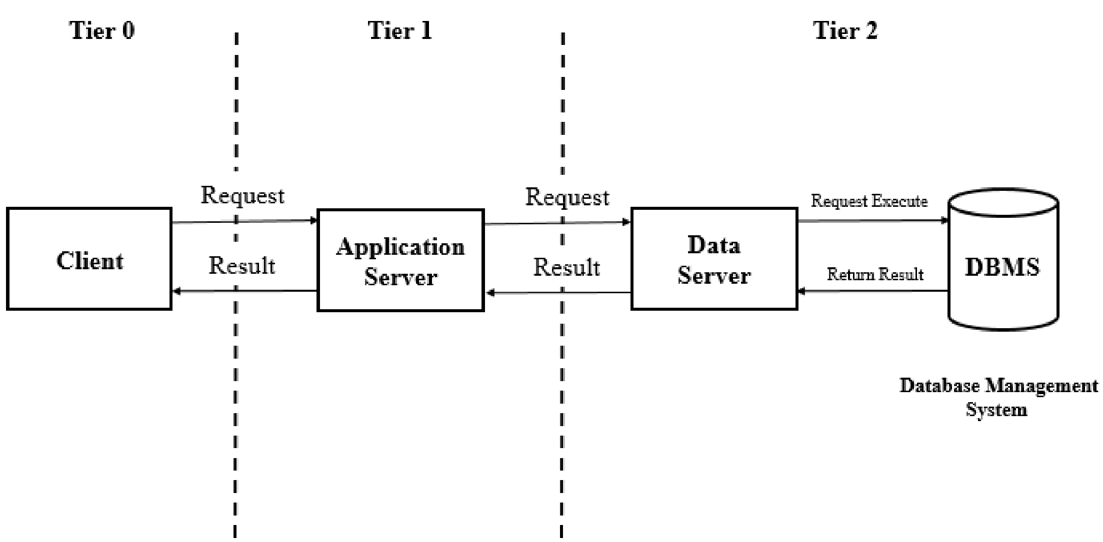

Figure 2.3 Three-tier client-server architecture request/response flow

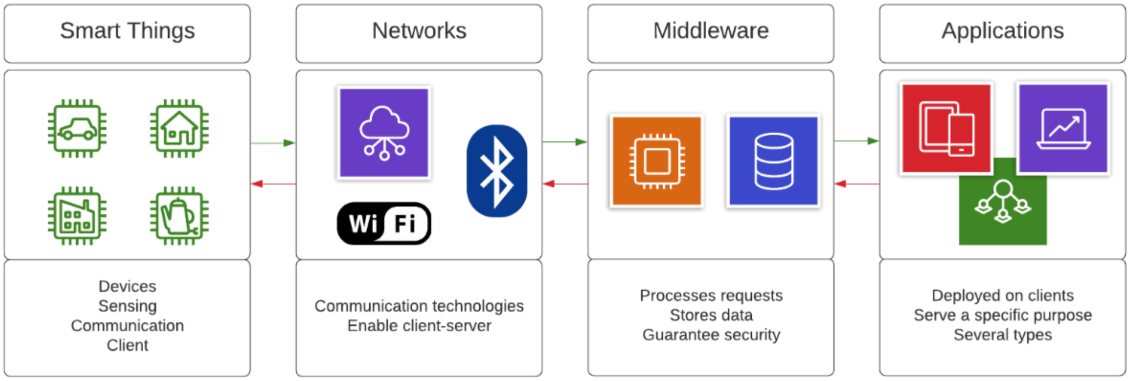

Figure 2.4 IoT basic services and layers

Table 2.1 Elements part of an OHSMS system.

General elements (Redinger & Levine, 1998)	Mining focused elements (CORE SAFETY, 2015)
Management commitment and resources.	Leadership Development
Employee participation.	Responsibility and Accountability
Occupational health and safety policy.	Management Systems Coordination
Goals and objectives.	Fatality Prevention / Risk Management
Performance measures.	Training and Competence
System planning and development.	Emergency Management
OHSMS manual and procedures.	Culture Enhancement
Training system.	Collaboration and Communication
Preventive and corrective action system.	Reinforcement and Recognition
Procurement and contracting.	Resources and Planning
Communication system.	Change Management
Evaluation system.	Work Procedures and Permits
Continual improvement.	Occupational Health
Integration.	Incident Reporting and Investigation
Management review.	Behavior Optimization
	Safety and Health Management Assurance Assurance

Table 2.2 Employer and employee responsibilities (Theron, 2014).

Responsibility	Employer	Employee
Educate	Inform employees; Provide training	Be familiar with risks; Understand how to reduce risks
Identify	Identify risks; Establish a monitoring system to identify problems	Report any identified risk; Contribute to establishing monitoring systems
Assess	Assess and control risks; Ensure that no practice contributes to a risk	Cooperate with control measures; Manage individual factors

Table 2.3 General, mental, and muscular contributors to fatigue (Techera et al., 2016).

Factor	Definition	Impact
Sleep deprivation	Sleep deprivation refers to a loss in the amount of consecutive hours of sleep.	General
Mental exertion	Sustained cognitive activity that requires extraordinary mental effort.	Mental
Muscular exertion	Exhaustion of the muscle due to an extent period of sustained tension or repetitive activity.	Muscular
Workload	High physical or mental demands at work.	Mental, General
Overtime and LWH	"Overtime" is the amount of time worked that exceeds 40 h of work a week. LWH is defined as working more than 8 hours on a single shift.	Mental, General
Incomplete recovery	Recovery is the process of reverting or reversing the negative effects of job demand to return to a pre work state.	Mental
Work environment	Noise, light intensity, vibration, and temperature are all environmental factors linked to fatigue.	Mental, General
Social environment	The quality and characteristics of worker relationships with peer and supervisors, as well as the perceived freedom at work.	Mental
Emotional predisposition	Emotional disposition pertains to the level of fear, stress, or overall attitude a worker has toward a certain task or job.	Mental

Table 2.4 Raw data from yes/no task example.

		Response event		Row
		Yes	**No**	**Sum**
Stimulus event	**Present**	150	50	200
	Not Present	40	60	100

Table 2.5 Probabilities based on yes/no task raw data.

		Response event		Row
		Yes	**No**	**Sum**
Stimulus event	**Present**	$P(S\|s) = \frac{150}{200} = 0.75$	$P(N\|s) = \frac{50}{200} = 0.25$	1.0
	Not Present	$P(S\|n) = \frac{40}{100} = 0.40$	$P(N\|n) = \frac{60}{100} = 0.60$	1.0

Table 2.6 Karolinska sleepines scale (Åkerstedt & Gillberg, 1990).

Karolinska sleepines scale (KSS)	
Extremely Alert	1
Very alert	2
Alert	3
Rather alert	4
Neither alert nor sleepy	5
Some signs of sleepiness	6
Sleepy, but no effort to keep awake	7
Sleepy, but some effort to keep awake	8
Very sleepy, great effort to keep awake, fighting sleep	9
Extremely sleepy, cannot keep awake	10

Table 2.7 Output expected from different IoT applications (Molaei et al., 2020).

Output	IoT Application
Monitoring system	Coal Mine gas wireless monitoring system based on WSNs Coal Mine Monitoring System Ventilation Monitoring
System	Underground Mine Air Quality Pollutant Prediction Coal mining employee positioning system
Model	Reliability evaluation of Coal Mines using Internet of Things Sensing, Monitoring and Prediction of Underground Mines Roof Support

Table 2.8 Wrist wearable devices and application capacities (Mardonova & Choi, 2018).

Device	Application
Fitness tracker	Occupational health monitoring Occupational disease prevention
Smartwatches	Mining equipment management Process monitoring and logistics management Communication and data management
Medical wearable devices	Occupational health monitoring Occupational disease prevention Operational safety

CHAPTER 3

MATERIALS AND METHODS

This chapter covers this study methodological approach, and it explores the following: variables of interest, materials developed and used, technologies, business rules, and proposed data analysis. It explains the decisions that were taken for the study as well as the logic behind the way that it is structured. The Plan, Do, Check, Act approach provides the core methodological approach due to its use on management systems such as the one proposed. The PDCA model emphasizes on continuous assessment to create continuous improvement of the system and is briefly summarized in the following points (CORE SAFETY, 2015):

- Plan: define the scope of the system by establishing objectives and processes necessary to deliver results in line with your organization's policies.
- Do: Implement the system structure and ensure that the involver actors know how to deal with it.
- Check: monitor and measure progress against your policy, objectives, report the results, and verify if the system works as designed.
- Act: act to correct the system and/or improve its overall performance.

The initial step is the user interface design which involves defining a simple tool capable to execute the necessary assessments. After defining the interface, it is necessary to identify which variables need to be collected. Chapter 2 provides the base behind the decision to collect subjective sleep levels, reaction times, dates, and times of assessments from each person involved in the study. Defining the variables of interest provides information to design a data structure and tools to handle them.

Section 3.2 covers the tools developed, their responsibilities, and technical details. For this case study, different tools were custom built to achieve the expected results, to simplify their understanding and functions each tool is covered individually. It also explains business rules included in the system and how the middleware and communication layer works, showing technical aspects such as client-server specifications, offline scenarios, API, and other necessary tools.

Lastly, section 3.3 explores the proposed statistical/mathematical approach to analyze the variables of interest. The expected product is the capacity to build a user baseline and to have better understanding on how reaction time and sleep levels fluctuate throughout an operational day in a mine site.

3.1 Plan

During the planning phase of the PDCA cycle the user interface necessary of the system was designed trying to achieve a simple tool capable of executing the assessments throughout an operational shift. For that matter, the number of interactions from operators with the application was kept to a minimum and the only expected interactions are opening the application during the beginning of the shift and answering the assessments when prompted. The application only shows the time of day in its default state to avoid distracting operators or causing them to want to interact with it. The final interface is presented on Figure 3.1 and consists of application icon on the smartwatch (1), default screen (2), assessment question screen (3), KSS assessment screen (4), confirmation screen (5), PVT assessment screen (6, 7, and 8).

The base of this study lies in KSS, SDT, and PVT data; Therefore, the identification process is straight forward and revolves around collecting data based on these theories and the collected variables and the theory that they relate to are shown on Table 3.1.

To gather the identified variables a relational database hosted on Amazon Relational Database Service (RDS) stores all incoming data. A relational database is a type of database that organizes data into tables that can be linked to each other, these tables can be either dimension or fact tables.

Fact tables store mainly numerical information, when there is the need for descriptive information it generally links to a dimension table (IBM Knowledge Center, 2021). For this research there are two fact tables: question and reaction which stores sleep levels and reaction time measurements, respectively.

On the other hand, dimension tables store information about the facts and tends to have descriptive information, in this case the identifier table is the only dimension table and it contains descriptive information for the user (IBM Knowledge Center, 2021).

The main advantage of using a relational database is the capacity to relate entities to data, avoid repeated data input, and achieve insights between different tables (IBM Cloud Education, 2021). Figure 3.2 shows the entity relationship diagram, which shows both fact and dimension tables, their respective fields and relationships. It is evident that there are more fields than variables of interest, this happens because when designing the database, it is necessary to translate the concept of what these variables of interest mean into actual database fields. One example is the reaction table that has state and click fields to translate hit and correct rejections into the system.

The database system chosen for the study was PostgreSQL. PostgreSQL is a powerful, open-source object-relational database system with over 30 years of active development that has earned it a strong reputation for reliability, feature robustness, and performance (The PostgreSQL Global Development Group, 2021). The data characterization of the database is presented in Tables 3.2, 3.3, and 3.4. The characterization shows the database fields, their descriptions, and variable types. It is necessary to characterize the data to make sure that the correct type of data is input in each column and to document the database design process for future research and/or users. It also provides a better understanding of the data from an analytical perspective, making it easier to aggregate and manipulate data in future steps.

As a support mechanism, the application server backs up all the received data in text files after its information has been persisted into the database. The system saves the data into AWS Simples Storage Service (S3) as raw .csv files containing the original data persisted on the database. For each reaction test taken the system creates a new file; Therefore, each user possesses several reaction test files stored in a folder that contains their data. For sleep levels data, the system creates a single file per user that updates once it receives new information, maintaining a history of sleep levels throughout different days.

To identify backup files, and access them, if necessary, the system follows a naming convention based on user identifiers, type of file, and date. For files that store fatigue levels, the naming convention is fatigue + underscore + user id + .csv. On the other hand, files containing reaction time test data follow the naming convention: reaction + underscore + user id + underscore + timestamp of the first assessment in the test (in milliseconds) + .csv. As an example consider the user identifier 86X2XW, that has one of his first reaction time assessment on Tuesday, December 1, 2020 10:55:40 PM GMT-07:00 (1606888540000 milliseconds following Unix time convention) his fatigue and reaction files for this scenario would be fatigue_86X2XW.csv, and reaction_86X2XW_1606888540000.csv respectively.

One must also consider that the original data follows JavaScript coding patterns and formats; Therefore, the data that follows the application format needs to be pre-processed due to format differences between the application layer and the middleware layer, which is responsible for persisting the original data into the database. The original data follows the JavaScript Object Notation (JSON), and the date and time fields follow ISO8601. Fatigue levels and reaction times are formatted as shown in Figure 3.3 and Figure 3.4, respectively.

If a different data format is provided, the middleware layer will identify it and will not allow it to be persisted into the database. All the fields need to be filled to guarantee that no null values are saved and that only data that conveys information is stored, preserving the database integrity. This general strategy also guarantees increased security for the designed database.

3.2 Do

During this phase, what was planned in the previous phase is executed to achieve the desired goals (Wang, 2017). Considering that during the planning phase the application was designed and variables of interested identified, the tools necessary for an integrated system to operate are developed in this phase.

Considering an IoT architecture (see 2.4.2) the development process breaks into the following: application and sensing, sensing and security, middleware. The decision to aggregate application and sensing as part of the same development process happens because fitness trackers are used; Therefore, while the application is being designed the sensors and hardware that provides the raw data are accessed but lack an identifier. The lack of identifiers leads to aggregating sensing and security, in this development process a strategy for user and device identification is created and this also prevents users that have not gone through the authentication process to use the developed tools. Finally, the middleware layer hands all incoming data, and pre-processes and persists it in the database for further analysis.

3.2.1 Sensing and application layer

The first step after database design was to develop a fitness tracker application that could handle custom code, and data. For this purpose, Fitbit Versa 2 devices were chosen due to a number of reasons such as: available sensors, custom application programming interface (API), capacity to handle custom JavaScript code, and ease of deployment.

The Versa 2 application, named Real Time Fatigue Management (RTFM) provides the core of the study. The application is responsible for assessing individual operator fatigue levels, and reaction times and was developed in JavaScript programming language with the aid of the Fitbit Software Development Kit (SDK). One of the advantages of using an established SDK is the capacity to exploit built-in sensors in an effective way. Other than that, utilizing an out-of-shelf fitness tracker enables the use of the company's established measurements and analysis such as: sleep quality, activity, and heartbeat for example as well as their own application to setup the device and its sensors.

The RTM app is responsible for conducting both short PVT test and assessing sleep level based on the KSS. It asks operators every 2 hours ± 10 minutes to take both assessments, the first one being the KSS and the second one the short PVT. If operators are unavailable at the time that the tool asks them to take the assessment, they can take it later. To guarantee that they do it, the tool reminds operators every 5 minutes by vibrating the haptic motor of the device. The reminder is one of the strategies to ensure that operators take the test, it also ensures that they have the capacity to take the test later if they feel unease when first asked.

Before starting the application use, a onetime setup process is necessary to guarantee that every device is identifiable since this is one the principles behind IoT. For the application setup, users need to authenticate through the security layer (see 3.2.2) to receive an identifier and input it in the application settings as shown in Figure 3.5.

During the assessment, the operator first answers their subjective fatigue level according to the KSS scale, confirm the fatigue level, and starts a shortened PVT test. The PVT test exposes operators to visual stimuli 20 times, if the stimulus is green, they must tap the device's screen, if red, they must wait. The application measures three parameters: if the operator pressed the screen, the state that the screen had, and the amount of time that it took for the user to tap the screen (measured in milliseconds). Each stimulus happens in random intervals ranging from 1 to 2 seconds.

JavaScript Math.random function is a stable function that is responsible for changing the screen between states and is used because the Versa 2 device supports it. The function generates a random number between 0 and 1 which acts as a threshold for changing screen states.

The screen alters between three basic states: red, green, and loading with green behaving as the signal, red as noise, and loading as an interval between each assessment and to record miss taps. The code is responsible for changing the color of the screen and its internal variable state, if the number is lower than 0.75 the screen changes to green, on the other hand it changes to red. with. Figure 3.6 details the logic behind the getState function which is the responsible for altering states in the application

To ensure ease of use the only command/interaction with the application other than the assessments is when operators need to open the application in the beginning of the shift. After opening the application, a standard clock will be available and no other information is shown in order to minimize the interaction with the smartwatch. Once the programmed time has passed, the application buzzes and asks the operator to take the assessment as previously explained. After 6 assessments/shift or 12 straight hours of use, the application closes itself and persists any unsaved data in the database.

To guarantee that operators only take assessments when they are safe, training sections were held with them. Other than that, the whole assessment was designed to last no more than 3 minutes so that they can take it while taking a small break or when haul trucks are loading and/or dumping material for example. This design strategy was taken to ensure operators safety, as this is one of the main purposes of a mining operation.

Figure 3.7 demonstrates the logic behind the RTFM application and how operator should interact with it. It is also part of the support and training material that was provided to operators and managers to guarantee a standard operational procedure (SOP).

3.2.2 Sensing and security layer

As Versa 2 devices hardware lacks unique identifiers available for use, a tool was developed to uniquely identify each device and to ensure the middleware's security. Uniquely identifying each device gives the capacity to aggregate data to an individual level. In order to do so, the Fitbit user id, which is a unique user identifier composed of six alpha numeric characters available in the Fitbit system is extracted via an authentication process.

The authentication process takes place in a webpage designed exclusively for that reason and it also helps to explore data available from third party applications such as the sleep data collected by Fitbit if there is the need for it. The webpage guides users through the authentication process and was developed using HTML, CSS, Kotlin, and JavaScript.

The authentication front-end process is straightforward. First, users navigate to an URL provided to them. Considering that this study involved more than one site, each of those had a different address in their training material to identify the user's company during the authentication process.

Once in the webpage, users enter a research identifier that is composed by their first name, last name, and date of birth i.e.: Considering João Marques born on November 13th, 1992, the research identifier is: JM111392. After inputting the id of the user twice (to guarantee that no misspelling occurred) the user is directed to the Fitbit authentication page, where they grant permission to access their data.

Finally, the user receives their user id which will be used by the RTFM application in the data capture process. During this process, the middleware layer also stores the information necessary to communicate with Fitbit servers in the identifier table. A brief summary of the process is shown on Figure 3.8. Detailed information is provided on 0 since it focusses on deployment.

3.2.3 Middleware layer

The application server, developed in Kotlin, and utilizing the Spring Boot framework is the responsible for managing all the business rules, and communication with the database. The server is hosted on Amazon Web Services (AWS), to ensure availability, and scalability. The main services from AWS used in the system are shown in Figure 3.9 and detailed below:

- Elastic Cloud Computing (EC2): provides a virtual machine responsible for hosting the application.
- Simple Storage Service (S3): provides a cloud-storage service that has the capacity to save files and serve them when necessary.
- Relational Database Service (RDS): provides a scalable database.
- Elastic Beanstalk (EB): provides an application deployment service to handle changes and change any application configuration.
- Route 53: provides a routing service that redirects the original application URL to a hosted domain.

The middleware layer provides endpoints that receive information from the RTFM app in the form of an API. An endpoint is a communication channel that expects a certain type of information, when the information is received it executes pre-designed commands and finishes by sending a response back. The communication channels follow the HTTP protocol (MDN Web Docs, 2021), and expects structured data as described in Figure 3.3

and Figure 3.4. Other than HTTP protocols being the standard communication protocol, it also provides developers with a variety of established response codes that can be easily understood.

The middleware API's responsibilities consist of the creation, read, update, and deletion (CRUD) of data. Before doing any mentioned operation, the middleware verifies data-format of every request sent from the clients before sending it to the database and

AWS S3 services. The middleware is also responsible for communicating with Fitbit servers to authenticate users in the system. When users input their research id in the developed webpage a request sent to the middleware that handles communication with Fitbit via an OAuth authentication protocol (Hardt, 2012). This type of authentication protocol is an internet standard used when two middleware need to communicate to each other in a secure manner that preserves user data as shown in Figure 3.10.

The final middleware responsibility is the creation and maintenance of the database. Previously, the database design was established but its creation is still missing. To create the designed database an object-oriented approach was used, this means that the middleware translates each table as individual Kotlin scripts/classes.

The Kotlin code is converted to structured query language (SQL) via the Spring Boot framework used during development. This means that the queries used to create the server are handled via a robust framework with years of development and it ensures that a variety of rules are followed to create and update the database. It also facilitates database maintenance and migration if there is a design change.

3.2.4 Communication layer

Since mine sites tend to have connectivity limitations one must have this on mind when developing systems for data collections and analysis. This section details how the tools developed communicate to each other. For the purpose of this section, the sensing and application layer is referred as the client and the middleware as the server.

The system follows a 3-tier client-server architecture as shown in 0 and for that reason, all data sent from the client is processed by the server before going to the database. This layer also covers the technologies responsible for sending data and enabling communication between different tools. Considering that the main client is a Versa 2 device, the technologies necessary for communication are mainly: Bluetooth, Wi-Fi, 4G, and cloud services. These technologies provide simplicity and the ability to make use of what is already established in a surface mine. Even in the case of an offline scenario such as an underground mine, the application was designed to collect data and transmit it when connectivity is restored, such as in the end of the shift. This approach affects data visibility as soon as collection happens but ensures that data is stored and transmitted properly.

Other than the communication between layers, this section covers the business rules that the client and server follow. All data generated by the client is a result of the assessments taken and any additional client data originates from the sensors available on the Versa 2 device. An existing limitation on the Versa 2 devices is that they depend on a Bluetooth communication with a smartphone to send data; Therefore, if Bluetooth is not available, data will only be sent when these conditions are met.

At the end of each assessment the RTFM app generates two text files in the fitness tracker, one for the sleep level, and one for the reaction test. Once text files are created, two requests are sent to the server's communication channels shown on Table 3.5, one for the sleep level, and the second one for the PVT test.

At this point the system faces the first business rule which consists of verifying if the client has access to the communication layer to send the request to the server. If there's no access the client stores the text files and waits until there is communication to sync them. If they are sent but the response code different from 200 (OK), it stores the files and tries to sync them at another opportunity. On the other hand, if the response is 200, the client deletes the text files because this means that the data was safely stored in the database and in AWS S3.

The client waits for the response because the fact that the request went through does not mean that the data was saved properly or that the server received it. To ensure proper communication, a response is necessary, and its code represents what happened; Therefore, the only status code that interests the client is 200, any other number would mean that a problem occurred in the communication process; Therefore, deleting the files before the final response is received, could lead to data loss.

Initially, each client would have only one file for sleep levels and one for PVT assessments but due to hardware limitations of the fitness tracker, the file strategy shown in 3.1 was put in place in the client and it was later translated to the server, to send smaller requests at a time. This disadvantage was one of the first identified and it required a change in the development process to overcome it.

As stated, the server is responsible for checking several business rules after the request is received in order to persist information on the database and decide on which response is appropriate. The first check is the data format, if by some reason the communication channel address is correct, but the data format does not follow the expected, the server will not persist the data and will respond with a bad request code represented by the number 400.

The second check is for the user identifier. In case that users have not gone through the authentication process, their requests will have a null value in the fitbit_id field. If this happens, the server will not allow this data to be persisted due to the lack of identification. It will still reply with an OK status code because this means that the server was able to analyze the received data, but it did not comply with the business rules put in place, signifying that there was a problem in the client setup. This response ensures that the client does not repeat this same incorrect request.

The third check is for repeated data, if by some reason the data was already saved but a problem occurred in the communication between client and server and the data was sent again, the server filters it based on the user that sent the data and the date and time on it. Since the RTFM app date and time creation is automated, there is no possibility that the same user has two entries that have the same time; Therefore, if the date and time already exists in the database, it means that the data was saved and there is no reason to persist it once again. The main difference here lies in the fact that the server will still respond with the code 200 after filtering the data. Finally, after the designed checks are executed, the data is persisted on the database via the Spring Boot framework. Having these checks ensure that only appropriate data is stored in the database. For the AWS S3 service, a Kotlin script generates the .csv files and is responsible for uploading them. The business rules presented in this section are summarized in Figure 3.11 diagram.

3.3 Check and Act

The last step in the methodological approach is the check and act phase. During this phase the management system is evaluated to identify if it is working as expected or not. If the system is not working as it was planned in previous phases there is the need to act and correct it to achieve what was initially designed.

During the check phase, there are two key approaches and analysis. The first one focuses on the system and identifying if it has the capacities it was designed to have. During this phase, any debugging to guarantee system stability is done and one constantly assesses how the system is working. The second approach relates to the collected data and results that the system is collecting.

Considering that there are three different theories used in this study the data will be analyzed in blocks which represent the standard approach used in evaluating each theory's result. The first step of interpreting the results is investigating via exploratory data analysis (EDA) in order to gain insights in how the collected data behaves and if there are any visible relations between each of the approaches taken.

Two tools are used for the analytical processes, PowerBI and Jupyter notebooks. PowerBI connects directly to the created database and creates a copy of the data that enables the capacity to investigate it in further detail. Upon connecting to the database one can create visuals that represent some information, apply filters to view only a part of the collected data, and create reports that can be shared with managers and researchers. Jupyter notebooks on the other hand are used due to some limitations that appear on PowerBI such as data manipulation and transformation as well as more complex analysis. These notebooks are based on Python code and are organized in a markdown notation that makes it easy to read, modify, and follow through. The used notebook is present in 0.

In the first stages, individual data is analyzed to provide an example on how to conduct the investigation. After this approach has been certified, aggregated data is explored to analyze the overall group results, similarities, and patterns. Since tests happen every two hours (approximately), the data will be summarized in interval of 2 hours to represent the development of sleep levels and reaction times throughout the day.

After preliminary results, the initial interpretation takes place and explores any relation or interesting outcomes from the collected data. The expected outcome in this stage is a better understanding of three points:

1. How test results change throughout an operational day.
2. How shifts influence test results.
3. If there are any relation between the results from one test with the other.

These three assumptions light enough questions to assess the data. Upon answering them and considering the data collected, system deployment, user training, technology possibilities and challenges, this study intends to answer the research objectives posed in 0. The research objectives are restated below to simplify the reading process:

- Explore workforce fatigue and reaction time in surface mines.
- Develop a deployment strategy for IoT application in surface mines.
- Provide a case study for I and II
- Show how low-cost out of shelf IoT solutions can add value to mining operations.

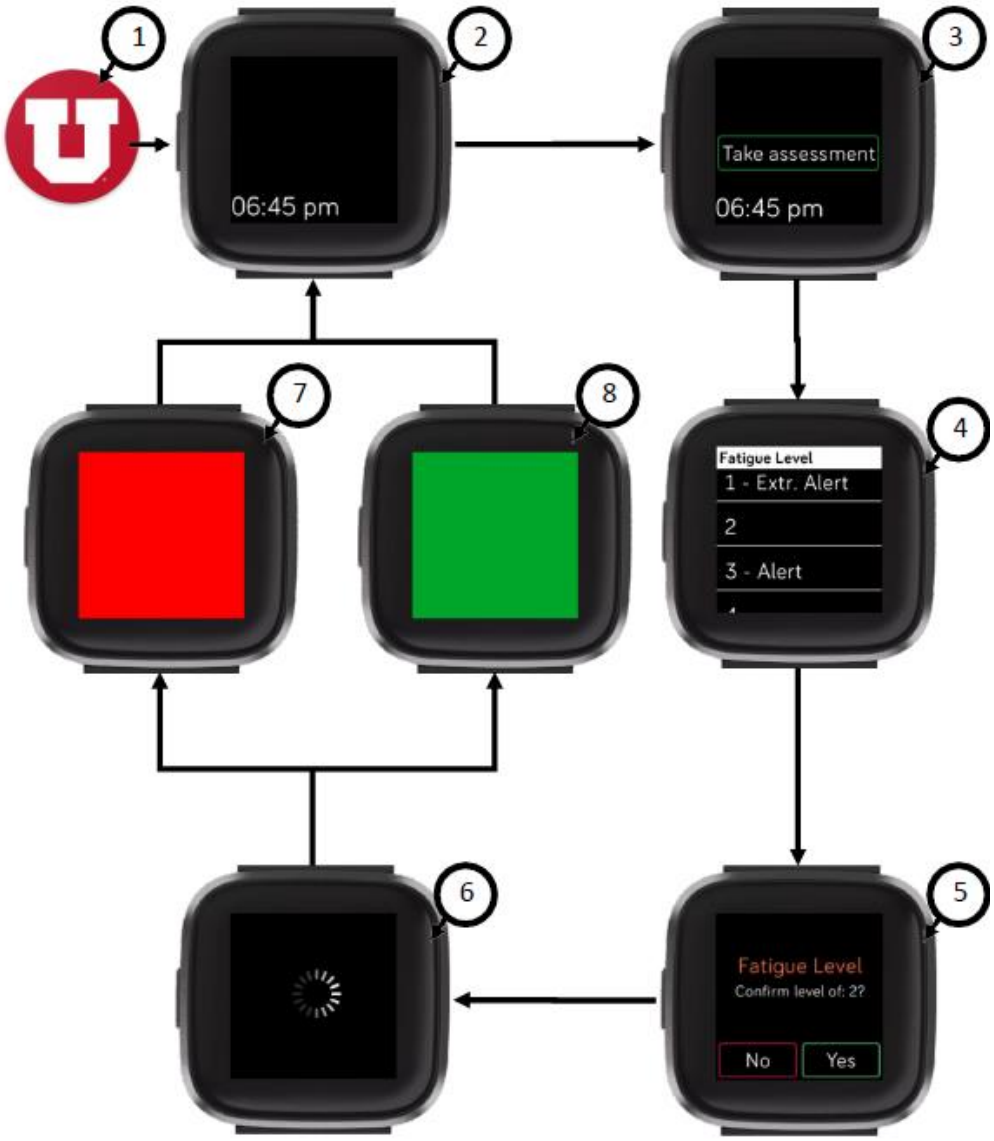

Figure 3.1 Final system interface

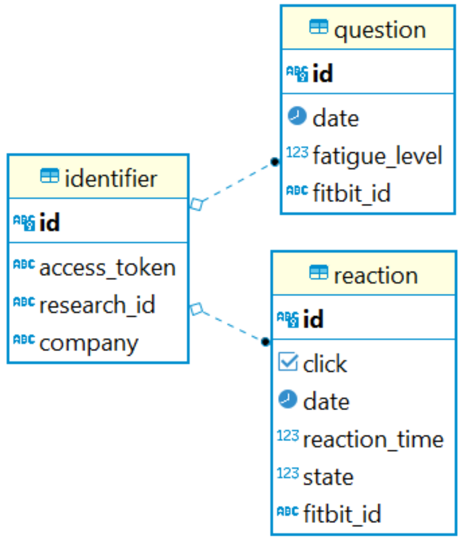

Figure 3.2 Database entity relationship diagram

```
{
    "id": String,
    "fitbit": {
        "id": String,
        "researchId": String,
        "accessToken": String,
        "company": String
    },
    "fatigueLevel": Integer,
    "date": "YYYY-MM-DDThh:mm:ss[.mmm]TZD"
}
```

Figure 3.3 Fatigue level data JSON format

```
[
    {
        "id": String,
        "date": "YYYY-MM-DDThh:mm:ss[.mmm]TZD",
        "reactionTime": Integer,
        "user_id": {
            "id": String,
            "researchId": String,
            "accessToken": String,
            "company": String
        },
        "click": Boolean,
        "state": Integer
    }
]
```

Figure 3.4 Reaction time data JSON format

1—Open Fitbit App

2—Select user profile

3—Select Fitbit device

4—Open App gallery

5—Search for RTFM and click on settings

6—Select user

7—Input the provided user

8—Click on save

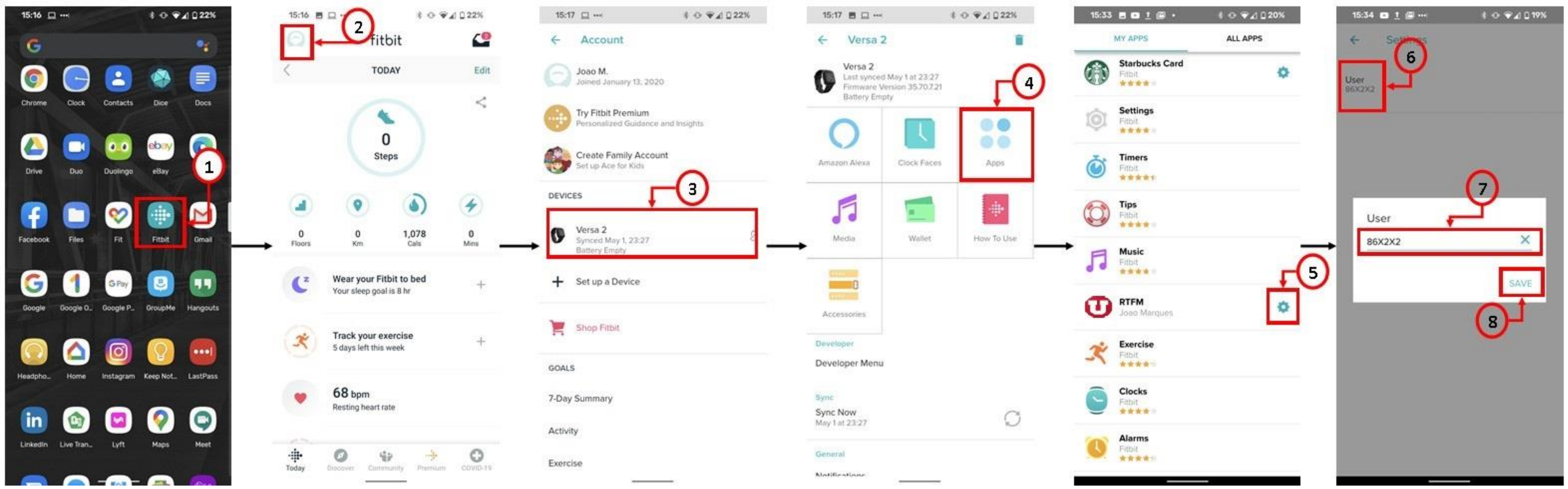

Figure 3.5 RTFM application setup

```
function getState(current) {
  if (current === 1 || current === 2) {
    return state_initial
  } else {
    if (Math.random() < 0.75) {
      return state_green;
    } else {
      return state_red;
    }
  }
}
```

Figure 3.6 Randomizing function

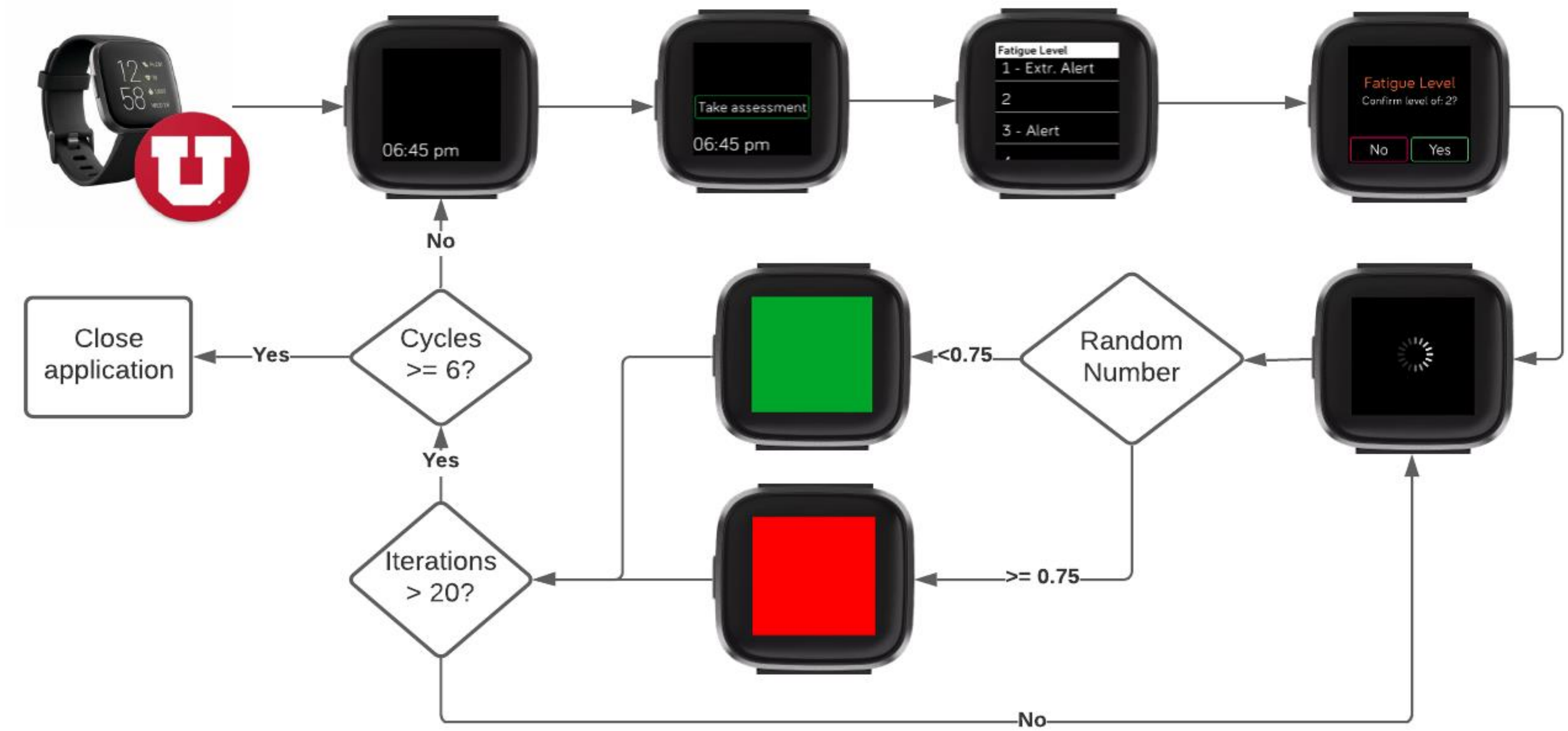

Figure 3.7 RTFM usability and logic instructions

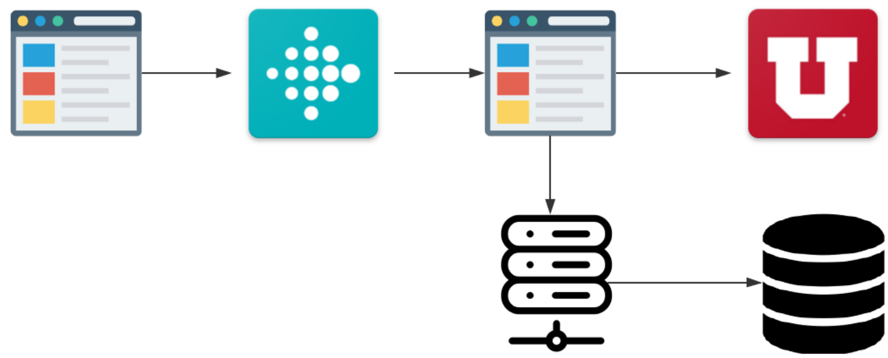

Figure 3.8 Web authentication process

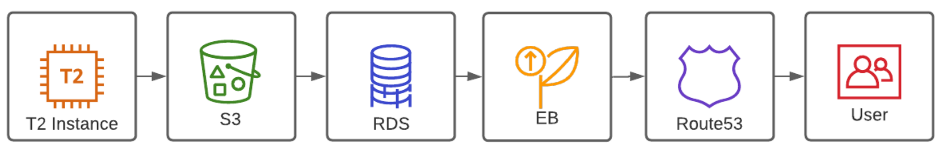

Figure 3.9 Middleware AWS architecture

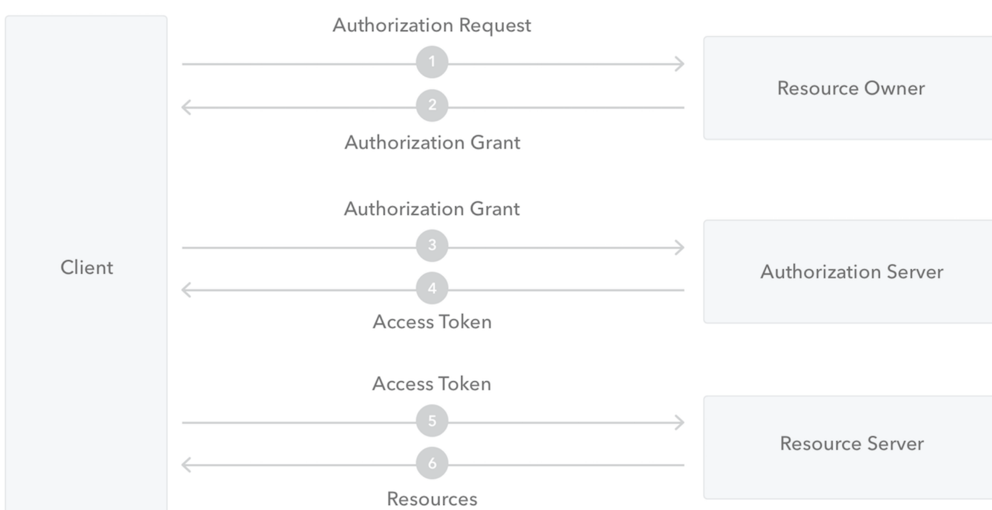

Figure 3.10 OAuth protocol process (Hardt, 2012)

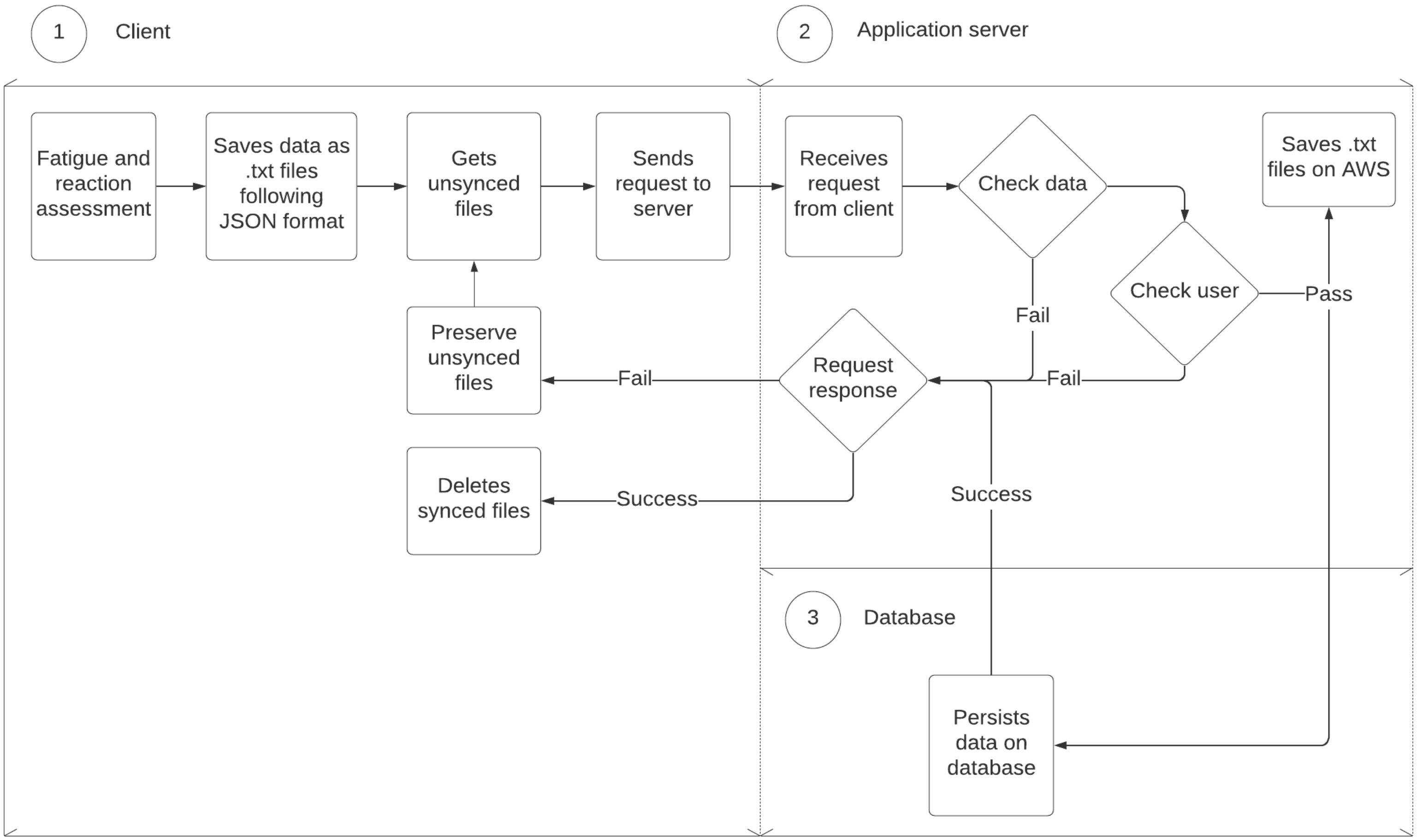

Figure 3.11 Client-server architecture business rules

Table 3.1 Identified variables of interest.

Theory	Variables
KSS	Sleep level
PVT	Reaction time
SDT	Hits and correct rejections
KSS, PVT, SDT	Assessment date and time
KSS, PVT, SDT	User identifier

Table 3.2 Data characterization of the identifier database table.

Field	Description	Type
id	fitbit user identifier that acts as primary key	Varchar
access_token	user access token that grants access to their Fitbit data	Varchar
research_id	custom research id to link data from Fitbit with the study	Varchar
company	company which the user belongs to	Varchar
date	date that the user was created	Datetime
last_login	last time that the user logged in the system	Datetime

Table 3.3 Data characterization of the questions database table.

Field	Description	Type
id	Primary key for the table	Varchar
date	Date and time that the assessment was taken	Varchar
fatigue_level	Measured fatigue level	Varchar
fitbit_id	Foreign key to the identifier table	Varchar

Table 3.4 Data characterization of the reaction database table.

Field	Description	Type
id	Fitbit user identifier that acts as primary key	Varchar
click	Boolean showing if the screen was clicked or not	Varchar
date	Date and time that the reaction assessment was taken	Varchar
reaction_time	Measured reaction time in milliseconds	Varchar
state	Represents the color of the screen in the moment of the assessment as an integer (1 – green, 2 – red);	Datetime
fitbit_id	Foreign key to the identifier table	Datetime

Table 3.5 Request's communication channels and executed tasks.

Channel	Task
https://app.umodelfatigue.com/api/question	Persists sleep levels
https://app.umodelfatigue.com/api/reaction	Persists PVT tests

CHAPTER 4

CASE STUDY

This chapter details the case study developed at a large surface mine to investigate the relation between subjective fatigue levels and measured reaction times in the mines' workforce. For this case study 40 Versa 2 devices were sent to the mine site. The following sections offer a deeper view in the study, focusing on the limitations and challenges, deployment of tools, troubleshooting, and training materials.

4.1 Debugging

After base tools initial development, a testing environment was set up to ensure that the tools were behaving as expected. Since the developed tools would be deployed in mine sites and would probably face connectivity issues this was considered during the testing period. To test the tools, the Utah Mining Operational Data Excellence Lab (UMODEL) research group advised by Dr. Pratt Rogers used the RTFM app for approximately 2 months (November to December 2020) to provide feedback on it.

During the test, data collection problems were frequent, and its investigation was mandatory before deploying the tools in the mine site. UMODEL's feedback was not able to provide detailed information to understand why the data was not being collected accordingly but provided essential feedback in terms of usability and changes towards application design such as language, interface, usage, and workflow. Since data collection problems were frequent, it was necessary to enable tools in the middleware to log requests and response to understand the issues that the middleware was facing. Upon enabling these tools, it was clear why data was not coming in as expected. Figure 4.1 shows a successful request/response log.

The first reason to draw attention was wrong application setup. Users were not configuring the RTFM application as expected and because of this were lacking individual identifiers registered in the fitness tracker. Due to the business rules put in place and to the lack of individual identifiers, when the middleware received the data, it was filtering it to avoid unidentified incoming data.

The second reason was a data format error between client and server. It was noted that the date and time format in the client was different from the server. Since date and time was sent in a format different from ISO8601, the server was not able to interpret it and was considering this data to be faulty, causing it to not be saved. This error log is shown on Figure 4.2 and the log divides in three blocks, yellow, green and light blue. The yellow block shows the request general error generated by the middleware, green shows the request received, and the light blue the response with a response code 400.

Finally, 6 assessments were expected per day but on several occasions less than 6 assessments happened. Further investigation was necessary, and this final unexpected behavior demanded monitoring server's logs and talking to the research group.

To investigate the matter two researchers kept track of their assessments in a daily diary which contained date and time of each assessment. This period last for a week and the conclusion was that in some days less than 6 assessments were taken. This fact is acceptable due to the logic behind the application, sometimes users were busy and/or could not take the assessment instantly, which led to intervals greater than 2 hours to happen, and consequently less than 6 assessments per day.

Table 4.1 shows the research diary kept during the one-week interval crossed with the database data to guarantee that all correct requests were due processed. Even though the data looks the same, they are from different sources, their similarities show that the collection process was done correctly.

4.2 Deployment

After the debugging stage completion, a deployment strategy was put in place in to start collecting data at the partner mine. Due to COVID-19 pandemic and the inability to visit mine sites, a remote strategy was put in place. For this strategy, the deployment phase was divided into three stages as shown in Figure 4.3.

The first stage was the pre-deployment. In this stage, meetings with managers and health and safety teams were held to align expectations and provide them with information regarding the research and the tools that would be used in the operation. During this stage management evaluates the tools to guarantee that it complies with health and safety standards and will not put operators at risk. As part of this stage, management reviews the developed training material that will be hand out to operators. The training material includes handouts, user instructions, and video content as shown in 0. After receiving green light from the management, the deployment phase starts.

In the second stage, or deployment, Versa 2 devices distribution and RTFM setup happens. The setup process follows the logic established on 3.2 and is composed of several steps detailed in the handouts given to operators. Considering the example of an operator working at Company A his instructions would be like the following:

1. Please download the Fitbit app to your cell phone (if you have not already) and set up your Fitbit user account (https://www.fitbit.com/), following instructions provided by Fitbit.
2. Install the RTFM app by clicking on the link below and following the instructions: http://app.umodelfatigue.com/install.
3. Go to the authentication webpage: http://app.umodelfatigue.com/install.

4. After being redirected to the Fitbit homepage login with your account.
5. You will receive a unique User ID on the webpage. Please enter this research ID on your RTFM setup page.

As part of this stage, online training sessions to instruct operators are held and they have the chance to ask questions or present any concerns about the research. An important topic is data privacy and usage and as stated in 3.1 operators need to be ensured that their data is not identifiable or provided to managers and supervisors on an individual level. After initial instructions, a period of a month is given for operator to setup their devices properly. Even with that time period, operators might still have difficulty in setting up their devices which leads to the third stage.

The third stage, or post-deployment is necessary for providing operators with technical support and ensuring that they can setup the device appropriately. In this stage the number of users in the system was constantly monitored via PowerBI reports as shown in Figure 4.4.

Constantly analyzing the number of users and how they interact with the system provides a metric for remote deployment, it also helps to monitor how many people have been using the application on a constant basis and identifying any abnormalities in the system. Additional to it, it is important to cross information regarding the number of sleep level assessment taken with the number of reaction tests recorded. An example of it is user 97KC8Y that for some reason has his PVT tests recorded but not his sleep levels.

The report shown on Figure 4.4 provides not only the number of users but also the number of PVT and KSS assessments taken throughout the day via the two bar charts present on the bottom of it. An important feature that it has is the capability of filtering the data on different intervals and from different groups. Analyzing the data in different time intervals provides key information on the deployment process and its stages.

Other than the bar charts, filters, and number of users, there is a table containing the earliest assessment from the users in the current day and the ratio between KSS and PVT assessments. The ratio between assessments shows if users are simply answering the KSS level and not interacting with the PVT test, which was a common issue in early stages and rose up when the data was analyzed as stated in the example of user 97KC8Y. The earliest and latest assessments provide an idea of the duration that users have the application open, this is important to verify if they are using the application throughout the day or closing it before it was expected.

In the post-deployment stage, Q&A sessions happens according to group meetings pre-established in the mine site. The meetings follow the mine's agenda and happens monthly. Due to the number of people involved in the study and to follow the mine scheduling they were divided in 2 groups, A and B; Therefore, every month after January 2021 had two meetings to follow up with operators.

In this stage, initial data analysis happens and provides researchers with basic insights regarding the study. For this initial data analysis, a PowerBI report shows the average aggregated fatigue level each hour of the day, average aggregated reaction time, and most importantly, the number of hits and correct rejections. The reaction time and sleep levels need a more detailed analysis but verifying on the number of hits and correct rejections provides a base to understand if the system is working as expected or if it needs calibration in terms of the number of stimulus per assessment and their threshold. Figure 4.5 shows the base dashboard used in monitoring the incoming data with a filter to analyze data from the last 2 weeks.

4.3 Limitations and Challenges

Upon defining the scope of the study and trying to move forward with it, the first challenge faced relates to the people involved in the study and the amount of information available. For this study, it was not possible to collect data from each participant involved in the study such as age, sex, experience, position, and several other inputs that can be valuable to the study of fatigue. Even though this does not impact the overall idea and the base of the study, it leads to simpler analysis due to the lack of these inputs.

Another factor that influences the study and is a constant challenge is the lack of information technology skills from the participants. Due to this factor and limitations posed by the COVID-19 pandemic, the deployment process turned to be a greater challenge than expected. This limitation is expected to show itself in numerical values in the results of the study when one analysis the deployment success in terms of deployed wearables and data collected.

An aspect that needs to be considered is the possibility of built-in bias due to the way that the test is structured. As time goes by participants might familiarize with the test, even though the literature review suggests that this does not happen (see 2.3.3), and even the order of questions might influence the results. Other than this, the participants belong to a mine rescue team, which tends to make them more aware of health and safety issues.

Lastly and possibly the major challenge that this study face is organizational issues. Mine sites sometimes show some resistance towards the implementation of new technologies and researching these. It was noted throughout the research that receiving support from mine sites and key personnel involved in the mine is of essence and in some cases that support can be hard to obtain in the expected levels. It was expected that this problem would show due to the way that mines operate and to cultural aspects in these operations, especially when it comes to management levels.

```
Jan 12 22:07:27 ip-172-31-37-174 web: 2021-01-12 22:07:27.137 TRACE 3473 --- [nio-5000-exec-9] org.zalando.logbook.Logbook:
    {"origin":"remote","type":"request","correlation":"b05c13bed7b4c973","protocol":"HTTP/1.1",
    "remote":"127.0.0.1","method":"POST","uri":"http://app.umodelfatigue.com/reaction",
    "headers":{"accept":["*/*"],"accept-encoding":["gzip, deflate"],
    "accept-language":["en-US,en-GB;q=0.9,en;q=0.8,pt-BR;q=0.7,pt;q=0.6"],"connection":["upgrade"],"content-length":["1916"],
    "content-type":["application/json"],"host":["app.umodelfatigue.com"],"sec-fetch-dest":["empty"],
    "sec-fetch-mode":["cors"],"sec-fetch-site":["cross-site"],
    "user-agent":["Fitbit/3.36 Android/30"],
    "x-forwarded-for":["73.59.82.212, 172.31.38.0"],
    "x-forwarded-port":["443"],
    "x-forwarded-proto":["https"],"x-real-ip":["172.31.38.0"],
    "x-requested-with":["com.fitbit.FitbitMobile"]},"body":
        [
            {"date":"2021-01-12T22:06:38.051Z","reactionTime":420,"click":true,"userId":"86x2xw","state":1},
            {"date":"2021-01-12T22:06:40.123Z", "reactionTime":424,"click":true,"userId":"86x2xw","state":1},
            {"date":"2021-01-12T22:06:41.965Z","reactionTime":0,"click":false,"userId":"86x2xw","state":2},
            {"date":"2021-01-12T22:06:44.597Z","reactionTime":0,"click":false,"userId":"86x2xw","state":2},
            {"date":"2021-01-12T22:06:47.847Z","reactionTime":0,"click":false,"userId":"86x2xw","state":2},
            {"date":"2021-01-12T22:06:50.780Z","reactionTime":428,"click":true,"userId":"86x2xw","state":1},
            {"date":"2021-01-12T22:06:52.670Z","reactionTime":431,"click":true,"userId":"86x2xw","state":1},
            {"date":"2021-01-12T22:06:54.945Z","reactionTime":428,"click":true,"userId":"86x2xw","state":1},
            {"date":"2021-01-12T22:06:56.845Z","reactionTime":459,"click":true,"userId":"86x2xw","state":1},
            {"date":"2021-01-12T22:06:59.302Z","reactionTime":390,"click":true,"userId":"86x2xw","state":1},
            {"date":"2021-01-12T22:07:01.418Z","reactionTime":374,"click":true,"userId":"86x2xw","state":1},
            {"date":"2021-01-12T22:07:03.418Z","reactionTime":481,"click":true,"userId":"86x2xw","state":1},
            {"date":"2021-01-12T22:07:05.126Z","reactionTime":482,"click":true,"userId":"86x2xw","state":1},
            {"date":"2021-01-12T22:07:07.407Z","reactionTime":0,"click":false,"userId":"86x2xw","state":2},
            {"date":"2021-01-12T22:07:10.791Z","reactionTime":415,"click":true,"userId":"86x2xw","state":1},
            {"date":"2021-01-12T22:07:12.929Z","reactionTime":414,"click":true,"userId":"86x2xw","state":1},
            {"date":"2021-01-12T22:07:14.804Z","reactionTime":402,"click":true,"userId":"86x2xw","state":1},
            {"date":"2021-01-12T22:07:17.115Z","reactionTime":0,"click":false,"userId":"86x2xw","state":2},
            {"date":"2021-01-12T22:07:19.964Z","reactionTime":353,"click":true,"userId":"86x2xw","state":2},
            {"date":"2021-01-12T22:07:21.947Z","reactionTime":409,"click":true,"userId":"86x2xw","state":1}
        ]
    }
Jan 12 22:07:27 ip-172-31-37-174 web: 2021-01-12 22:07:27.396 TRACE 3473 --- [nio-5000-exec-9] org.zalando.logbook.Logbook:
    {"origin":"local","type":"response","correlation":"b05c13bed7b4c973","duration":259,"protocol":"HTTP/1.1","status":200,"headers":
        {
        "Cache-Control":["no-cache, no-store, max-age=0, must-revalidate"],
        "Date":["Tue, 12 Jan 2021 22:07:27 GMT"],"Expires":["0"],"Pragma":["no-cache"],
        "Transfer-Encoding":["chunked"],"X-Content-Type-Options":["nosniff"],"X-Frame-Options":["DENY"],
        "X-XSS-Protection":["1; mode=block"]
        }
    }
```


Figure 4.1 Standard request/response log

```
Mar 19 22:57:03 ip-172-31-89-153 web: 2021-03-19 22:57:03.815  WARN 3522 --- [nio-5000-exec-2] .w.s.m.s.DefaultHandlerExceptionResolver :
Resolved [org.springframework.http.converter.HttpMessageNotReadableException:
JSON parse error: Unexpected character (',' (code 44)): expected a value;
nested exception is com.fasterxml.jackson.databind.JsonMappingException:
Unexpected character (',' (code 44)): expected a value
Mar 19 22:57:03 ip-172-31-89-153 web: at [Source: (PushbackInputStream);
line: 6, column: 9] (through reference chain: java.util.ArrayList[0])]
Mar 19 22:57:03 ip-172-31-89-153 web: 2021-03-19 22:57:03.815 TRACE 3522 --- [nio-5000-exec-2] org.zalando.logbook.Logbook               :
{"origin":"local","type":"response","correlation":"ff22ca65598aac1f","duration":1,"protocol":"HTTP/1.1","status":400,
"headers":{"Cache-Control":["no-cache, no-store, max-age=0, must-revalidate"],"Expires":["0"],"Pragma":["no-cache"],
"X-Content-Type-Options":["nosniff"],"X-Frame-Options":["DENY"],"X-XSS-Protection":["1; mode=block"]}}
Mar 19 22:57:18 ip-172-31-89-153 web: 2021-03-19 22:57:18.213 TRACE 3522 --- [nio-5000-exec-5] org.zalando.logbook.Logbook               :
{
"origin":"remote","type":"request","correlation":"fbf4f0de0e635dfb",
"protocol":"HTTP/1.1","remote":"127.0.0.1","method":"POST",
    "uri":"http://app.umodelfatigue.com/reaction",
    "headers":{"accept":["*/*"],"accept-encoding":["gzip, deflate, br"],"connection":["upgrade"],
    "content-length":["3261"],"content-type":["application/json"],
    "host":["app.umodelfatigue.com"],"postman-token":["e040c85f-5e76-4599-9cf0-37f631446a4f"],
    "user-agent":["PostmanRuntime/7.26.10"],"x-forwarded-for":["136.36.124.164, 172.31.38.0"],
    "x-forwarded-port":["443"],"x-forwarded-proto":["https"],
    "x-real-ip":["172.31.38.0"]},
    "body":
    [
        {"date":"2021-01-13T03:zz:38.049Z","reactionTime":453,"click":true,"userId":"86x2xw","state":1},
        .
        .
        .
        {"date":"2021-01-13T03:21:16.140Z","reactionTime":434,"click":true,"userId":"86x2xw","state":2}
    ]
}
Mar 19 22:57:18 ip-172-31-89-153 web: 2021-03-19 22:57:18.214  WARN 3522 --- [nio-5000-exec-5] .w.s.m.s.DefaultHandlerExceptionResolver :
Resolved [org.springframework.http.converter.HttpMessageNotReadableException: JSON parse error:
Unparseable date: "2021-01-13T03:zz:38.049Z"; nested exception is com.fasterxml.jackson.databind.JsonMappingException:
Unparseable date: "2021-01-13T03:zz:38.049Z" (through reference chain: java.util.ArrayList[0])]
Mar 19 22:57:18 ip-172-31-89-153 web: 2021-03-19 22:57:18.214 TRACE 3522 --- [nio-5000-exec-5] org.zalando.logbook.Logbook               :
{"origin":"local","type":"response","correlation":"fbf4f0de0e635dfb","duration":1,"protocol":"HTTP/1.1","status":400,
"headers":{"Cache-Control":["no-cache, no-store, max-age=0, must-revalidate"],"Expires":["0"],"Pragma":["no-cache"],
"X-Content-Type-Options":["nosniff"],"X-Frame-Options":["DENY"],"X-XSS-Protection":["1; mode=block"]}}
```

Figure 4.2 Defective request/response log

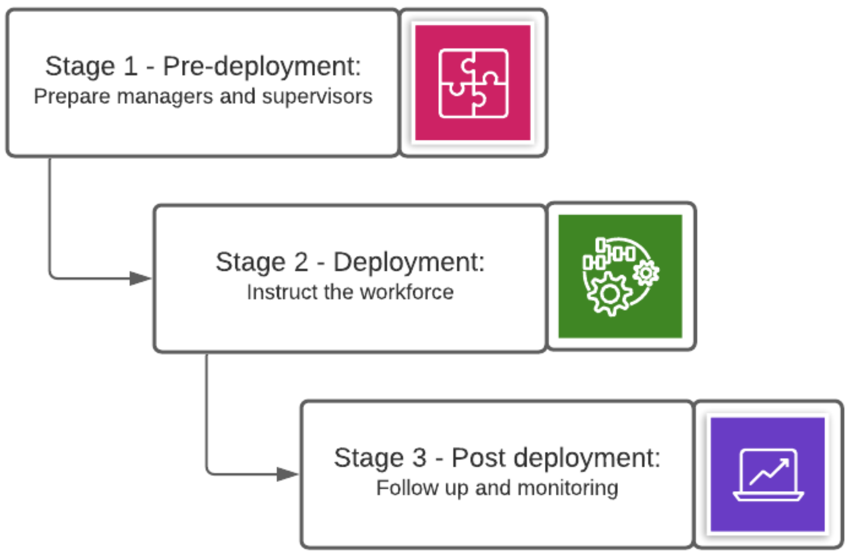

Figure 4.3 Three stages deployment concept

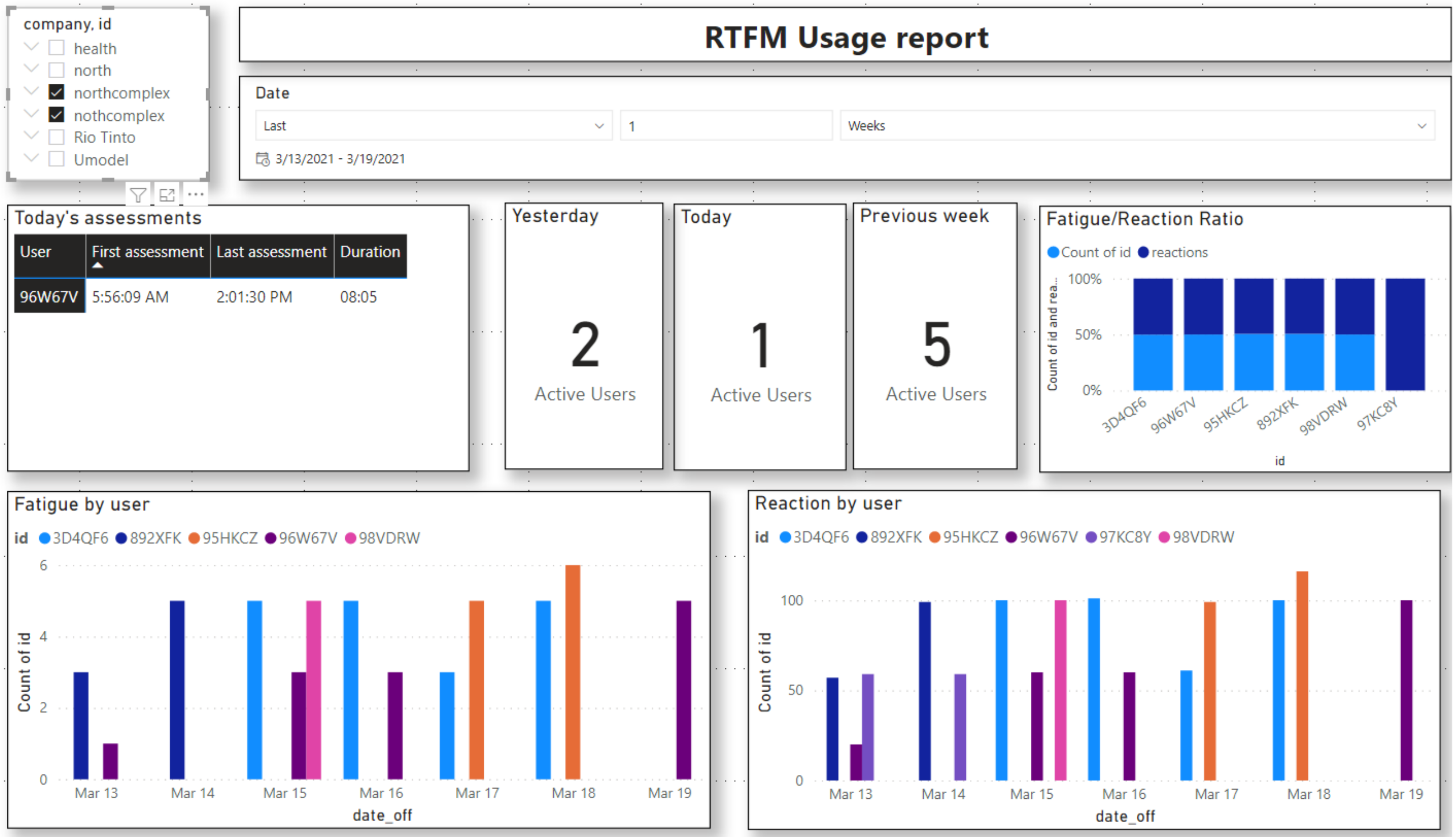

Figure 4.4 RTFM usage report

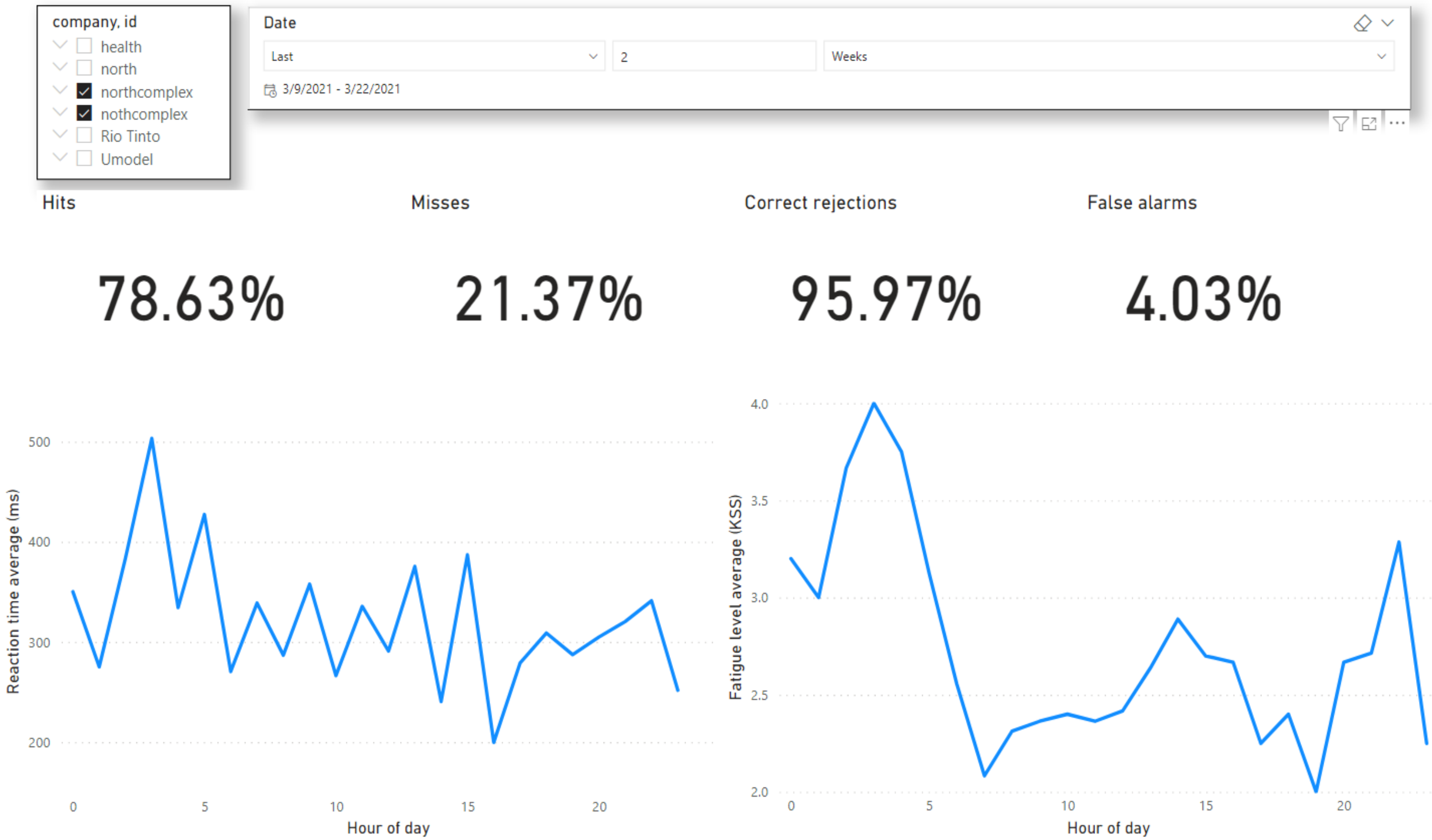

Figure 4.5 RTFM data monitoring dashboard

Table 4.1 Assessment diary example.

Diary data				Database data			
Date and time	**Fatigue Level**	**ID**	**Daily Count**	**Date and time**	**Fatigue Level**	**User ID**	**Daily Count**
01-12-20 7:04	6	7W8RMQ	1	01-12-20 7:04	6	7W8RMQ	1
02-12-20 7:28	5	7W8RMQ	1	02-12-20 7:28	5	7W8RMQ	1
03-12-20 0:27	3	7W8RMQ	2	03-12-20 0:27	3	7W8RMQ	2
03-12-20 2:36	3	7W8RMQ		03-12-20 2:36	3	7W8RMQ	
04-12-20 3:51	4	7W8RMQ	4	04-12-20 3:51	4	7W8RMQ	4
04-12-20 6:08	7	7W8RMQ		04-12-20 6:08	7	7W8RMQ	
04-12-20 8:15	7	7W8RMQ		04-12-20 8:15	7	7W8RMQ	
04-12-20 23:28	3	7W8RMQ		04-12-20 23:28	3	7W8RMQ	
07-12-20 0:05	3	7W8RMQ	2	07-12-20 0:05	3	7W8RMQ	2
07-12-20 3:39	4	7W8RMQ		07-12-20 3:39	4	7W8RMQ	

CHAPTER 5

RESULTS

This study has two sides to it that need to be considered when analyzing the results obtained throughout the case study, the first side considers the deployment strategy adopted to the study, site culture, workforce training and any subjective considerations. On the other hand, the study utilizes quantitative and qualitative data to investigate fatigue; Therefore, it is necessary to analyze the collected data over the period of the case study to conclude if it can help investigating and monitoring fatigue.

5.1 Subjective Analysis

This section explores the research group perception of the case study and explores some considerations that were observed in that time period. It is the result of meetings with managers, perceptions obtained in training sessions, communication with participants in the study and so forth. For easier understanding, this section breaks down into considerations about the deployment strategy, training sessions and materials, and overall site culture.

5.1.1 Deployment strategy

The chosen deployment strategy previously described was put into place due to identified site deployment limitations. After identifying how many devices were set up one can verify how many of those devices were actively collecting data on a constant basis. For that, 2 queries extract the results from the questions and reaction tables to verify which employees were able to not only authenticate on the website (sensing and security layer) but also in the RTFM app (application layer) and used the app constantly. The queries shown on Figure 5.1 both provide the number 13; Therefore, 52% of the participants properly utilized the application during the case study and had their data collected. Even though the adopted strategy was not the first option, by the end of the case study it showed interesting results and explains why even on modern days many companies go to the site to deploy even the simplest of technologies.

From the 40 devices sent to the mine, 25 were distributed and setup among operators. 40 devices were sent to the site, it was expected that not all of them would be distributed at first since not every employee would be able to participate in the study and the final decision of who would participate into it came from management and supervisors. Figure 5.2 shows the query used to extract the number of smartwatches set up in the site from the database.

Based on the results collected during the deployments phase, three types of users/operators were identified. The first type is the user that was not able to configure their smartwatch to work with the application properly, the second type is the user that was able to configure it but seems to not use in the expected way, and the last one is the user that was able to configure the application correctly and use it as expected. The second type was not expected since the application was thought to be easy to use, this type of user was identified through the assessment results. The results show that they answered their KSS assessment in the expected way but for some unknown reason did not answer their PVT test as expected. Figure 5.3 reflects the case of when a user answers their KSS assessment but does not take their PVT assessment.

This result shows that even with constant monitoring of the number of participants actively using the application, training sessions, and asking for support from managers, it was not possible to obtain a 100% deployment rate using the strategy put in place. On the other hand, this issue can be corrected with further training and/or visits to the site. A common trend noted is that participants were eager to help with the study and to use the developed solution but had difficulty on setting it up. This difficulty can originate from two possible sources, the first one being that the authentication and setup process is more difficulty than expected, and the second one is that the participants might lack some of the necessary knowledge to deal with IoT solutions.

The first reason can be improved by better application design, use of different techniques, and even a completely different setup. Training can also prove to be essential and solve many of difficulties that might show up, 0 shows the proposed training material for the developed system. A possible solution for the second case would be to have support from the site IT department and/or train employees that could act as ambassadors/leaders in order to improve the site safety standards and incorporate it into the existing OHSMS system.

A key takeaway in terms of deployment is the necessity to constantly communicate with managers and people involved with the study. Constant communication paved the road towards solving most of the problems that happened during the deployment stages. Even though the index of 52% is still far from ideal, this value was lower in the initial phases of the study and improved steadily as one moved from phase 1 to phase 2 and 3.

5.1.2 Cultural aspects and OHSMS integration

The second subjective topic of interest revolves around cultural aspects and how the developed system can be integrated in an existing OHSMS system. In terms of cultural aspects, as stated in other sessions of this study, even with extensive support from actors involved with the research, sometimes it was hard to overcome a barrier towards the implementation of new technologies in the site.

An aspect that drew attention was on how operators were supportive of initiatives to provide them with better information towards their own fatigue levels. It seems that it is easier to receive support from the workforce when the topic is health and safety. In terms of decision makers, the information gathered throughout meetings and communication is inconclusive in where they stand. In some cases, there was total support towards the study while in other cases it was harder to convince decision makers of the importance of researching and assessing fatigue.

Other than support from the workforce, another important aspect it how identifiable is the data. Considering that data collection happens by shift and teams, it can lead to management using collected data to assess operator's performance, which is undesired. The tool is designed to serve as a health and safety management tool and not to punish/assess operators.

When it comes to system integration and how this tool can incorporate in existing OHSMS's one believes that there are interesting possibilities especially in systems focused on risk management. Randolph (2015) in her work provides a detailed list of possible risks towards fatigue and how systems should address these to have better control over them. Based on the way that the system works, work scheduling and planning, and individual and non-work factors can be potential targets to an integration.

The mentioned areas are potential targets because with the data that comes from the RTFM one can use the collected information to store information related to how the work scheduling happens to try to improve it. Since the application runs on smartwatches with fitness tracking capabilities and the middleware is designed to interact and receive information from Fitbit servers, it can provide information such as activity levels, heart rate, and even sleep quality that could be used in an algorithm to deploy a better work scheduling strategy. Data collected from assessments, in addition to standard smartwatch sensors, can provide an indicator of when employers get close to an exhaustion point so that managers and supervisors can act before this happens.

Once again, cultural aspects show to be an important part of this tool since using the smartwatches out of the shift would be the ideal. Since fatigue can come from many sources such as mental, emotional, and physical, having a better idea of workforce habits out of the shift can provide indicators that are currently lacking in fatigue bio-mathematical models.

One understands that there are privacy concerns in using the smartwatch out of the mine, but the workforce can decide which permissions they give to the system and only data from the sensors would be used. To convince the workforce to use the devices out of the mine an incentive could be put in place such as flexible working schedule based on their current fatigue levels measured by the OHSMS system put in place.

The system is an open-source solution with a customizable API it makes it easy for companies to collect the data to a proprietary database if necessary. This aspect of the application allied to having the collected data in a traditional relational database makes the integration in already existing OHSMS possible. There is some value to the solution as a stand-alone tool but understanding how it can interact with existing tools might show where the real value to it lies. If companies want to utilize OHSMS as a tool for fatigue management they should try to incorporate different tools that can help assessing it, that can communicate to each other, rethink cultural aspects and provide adequate training for the workforce to guarantee the knowledge and use of the existing systems.

The findings reported in this section were expected and other studies such as Newton et al. (2002) corroborate that implementing an online deployment and training faces challenges that to a certain extent relates to cultural aspects. Newton takes a step further and cites that this type of strategy demands understanding of understanding of external influences, existing corporate goals, organizational culture and structures, and training goals and practices. Changing the mining culture when needed can not only provide safer environments but also bring other gains to the organization. A positive side to the need of improving cultural aspects and the necessity of training to utilize OHSMS capacities properly is that operators and the workforce tend to have a positive mindset towards it (Palka, 2017).

5.2 Analytical Analysis

This section explores the results obtained from the collected data over the period of approximately 3 months. Classical exploratory data analysis analyzes the results obtained and provide insights to understanding it and comparing the attained results versus what is available on fatigue related literature. Two tools were used in the exploratory data analysis. PowerBI was used in the initial stages of the analysis due to its simplicity and powerful capacities, it was also responsible for some of the data transformation necessary to other analysis. Jupyter notebooks coded in Python were used in later stages because PowerBI showed some limitations which forced the move to a different tool.

During the data transformation, 11 new columns were created to make the analysis easier, the new columns are:

1. day: day of the month
2. month: month of the year
3. year: year
4. hour: hour of day
5. minute: minute of the hour
6. second: second of the minute
7. time: time component of the date time
8. date_off: date component of the date time offset to a specific timezone
9. sdt: shows if the result of the reaction assessment was a hit, correct

rejection, false alarm, or miss.

10. dailyperiod: numerical value representing the period of day referent to the time column.
11. dailyperiodtext: text value representing the period of day referent to the time column.

To execute day-by-day analysis the day was broken down in 8 periods of 3 hours each. This was done to reduce the observed noise in the data and have aggregate the data in longer periods of time to clarify how was the workforce behavior over that period. Figure 5.4 and Figure 5.5 show the initial median reaction times and fatigue levels, respectively. These two figures show interesting results, especially when comparing reaction times with the fatigue levels, it is observed that they follow the same overall trend, the earlier and later hours of the day showing slower reaction times and higher fatigue levels.

A factor that draws attention on the average levels is the fact that the fatigue level in the KSS scale is never higher than 4, which according to the KSS would indicate that users are always at least rather alert. The participants in the study are volunteers and part of a mine rescue team which might influence their awareness towards fatigue and make them be more alert than usual. Since the fatigue level is subjective it is hard to tell if users feel that way or not. According to the data, it is possible to see that when there are peaks in the fatigue level the reaction time tends to get slower and, in some cases, it even surpasses the threshold of 500 milliseconds which can be considered as performance and/or attention lapses.

Figure 5.6 and Figure 5.7 shows histograms of the data and how both the reaction times and fatigue levels are distributed. Based on the presented histograms and from available literature on reaction tests it is possible to assume that the data follows an F-distribution (Hervey et al., 2006; Whelan, 2008). Figure 5.8 shows the distribution plot and corroborate the fact that the distribution is not normal but an F-distribution.

Table 5.1 shows basic statistics from the raw data and according to it 25% of the reaction times fall in the 75th percentile which surpasses the proposed threshold of 500ms. From the raw data, the final assessment relates to the number of hits and correct rejections. To calculate these the sdt column is used and gives the results shown on Figure 5.9 SDT results extracted from the PowerBI report and calculated via the SDT theory presented in 0.

A noticed aspect when checking the number of hits and correct rejections is that the percentage of hits was brought down by the type II users, the ones who were constantly answering the KSS assessments but were not taking the PVT test as expected. Even with the presence of these users, the index of approximately 90% and 95% for hits and correct rejections are good indicators that signal, and noise are being distinguished properly. It is important to note that operators were instructed to try to touch the screen the fastest that they could which could have led to an increase in the number of misses and false alarms.

The percentage of hits and correct rejections serve as a baseline of what to expect and can be used in cases that the operator takes an assessment is way below the expected rates of around 90-95% as a possible indicator of fatigue and/or inattention. After initial analysis with the raw data was finished, the data aggregated in periods of 3 hours was analyzed.

Results were not much different from what was initially observed and Figure 5.10 and Figure 5.11 show a similar behavior as the initial results. Overall, one sees that the period 09:00 pm to 06:00 am is the most sensible one which the presented literature on fatigue supports.

The final part of the analysis focuses on verifying the percentiles of the data aggregated in periods of 3 hours. To verify these one first looks at the box plots presented in Figure 5.12 and Figure 5.13 and then looks towards the results presented in Table 5.2 and Table 5.3. The boxplots lead to the same conclusions as before, while the percentile analysis show that in both hourly and period analysis the 60th percentile is where the threshold of 500ms lies.

The results provide a glimpse of what the RTFM system can achieve if it is integrated as part of an OHSMS system and receives more inputs. One input that is lacking and could prove to be essential is work scheduling which this study did not have access to. Having employees working schedule would enable more advanced analysis and possible identification on the impact of shift work and other practices common to the mining industry.

Even though this is a limited analysis, and it cannot answer the many questions related to fatigue it serves to provide some insight on the questions posed on 3.3. One of the key results and is the relation between reaction times and fatigue, especially considering the threshold of 500ms. The literature review suggests that smartwatches and touchscreen devices tend to be precise enough for PVT test; Therefore, even if there is a slight variation from the actual reaction to the measurement these values are still a decent indicative. Since the measured reaction times are acceptable the suggestion is that more inputs are fed to it to develop an indicator that is more informative to managers and decision-makers.

```
select count(id) from identifier where company = 'COMPANY A'
```

Figure 5.1 Query to extract the number of users authenticated in the system

```sql
select count(distinct(a.fitbit_id)) from question a
join identifier b
on a.fitbit_id = b.id
where b.company = 'COMPANY A'
```

```sql
select count(distinct(a.fitbit_id)) from reaction a
join identifier b
on a.fitbit_id = b.id
where b.company = 'COMPANY A'
```

Figure 5.2 Queries to check users that had their data collected

id	date	fatigue_level	fitbit_id
d4f6e5d6-04c6-4b22-b6da-2e824c2785f4	2021-04-19 09:52:51	1	4DR9DL

id	click	date	reaction_time	state	fitbit_id
a3245934-99eb-4481-b3ce-329b0b23660a	[ ]	2021-04-19 09:53:45	0	1	4DR9DL
b22832f5-7d3f-4cb0-bf1d-e4615d5216b5	[ ]	2021-04-19 09:53:42	0	1	4DR9DL
57c3a1fa-e35b-4bd9-9c34-8bf474a11b7f	[ ]	2021-04-19 09:53:39	0	1	4DR9DL
2dee521f-dd58-44ba-baac-1152fde66d22	[ ]	2021-04-19 09:53:36	0	2	4DR9DL
5ce3fda3-ff9b-406a-a9aa-10549a79f6b3	[ ]	2021-04-19 09:53:34	0	1	4DR9DL
2899794f-e39d-4352-8c80-5862d88895c7	[ ]	2021-04-19 09:53:30	0	2	4DR9DL
a41460b6-1153-48d6-b6a4-7c4afac0a542	[ ]	2021-04-19 09:53:28	0	1	4DR9DL
3c1c0781-fa49-43e6-9e86-f5ad58eb9ddd	[ ]	2021-04-19 09:53:25	0	1	4DR9DL
ef113360-7958-45e7-adbf-abc227955238	[ ]	2021-04-19 09:53:22	0	1	4DR9DL
37a1f766-da22-43ca-a39a-ff71ee136a54	[ ]	2021-04-19 09:53:19	0	1	4DR9DL
58a6e06f-f769-4081-b856-ca77c086570d	[ ]	2021-04-19 09:53:17	0	1	4DR9DL
07efeee4-756b-45ed-a0f6-b51de3b943ad	[ ]	2021-04-19 09:53:13	0	1	4DR9DL
c452b494-0d3e-4c0e-8f94-bba624035366	[ ]	2021-04-19 09:53:11	0	1	4DR9DL
f523f444-358c-4fbf-ac9f-6d2e4f38251f	[ ]	2021-04-19 09:53:08	0	1	4DR9DL
3885c586-c5b8-4354-a90c-77905ff81092	[ ]	2021-04-19 09:53:05	0	1	4DR9DL
e99c2bc9-428d-40c2-8974-c244a761ae8f	[ ]	2021-04-19 09:53:02	0	2	4DR9DL
81e3f9c1-f6f5-4c18-855f-72ffe30d1566	[ ]	2021-04-19 09:52:58	0	1	4DR9DL
8cb55fed-09a4-4cb9-85ea-256105bd340c	[ ]	2021-04-19 09:52:56	0	1	4DR9DL
74d69468-240f-449d-a952-79f7478786d4	[ ]	2021-04-19 09:52:53	0	1	4DR9DL

Figure 5.3 Failed PVT test assessment

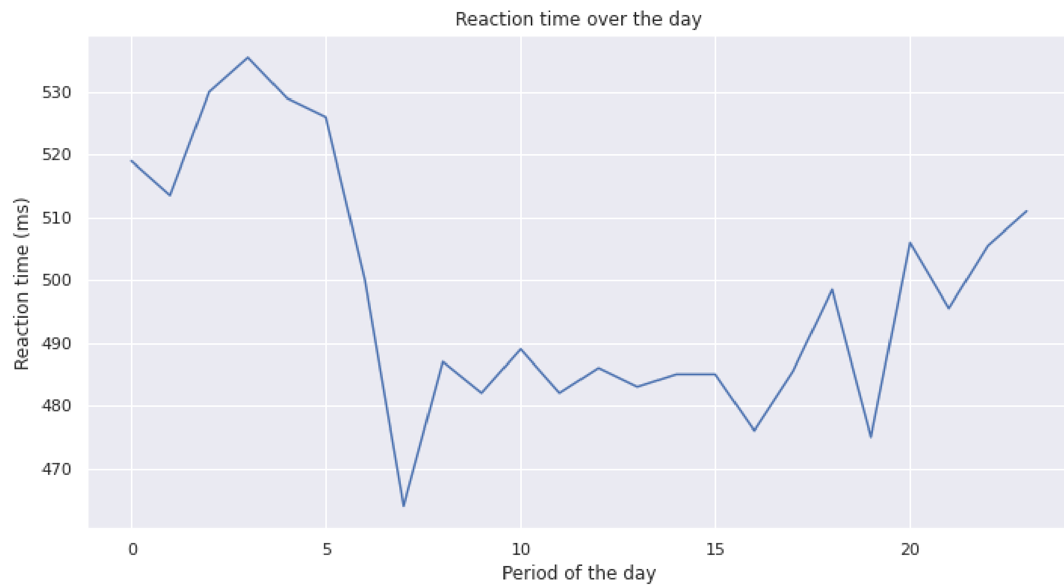

Figure 5.4 Reaction time over the day

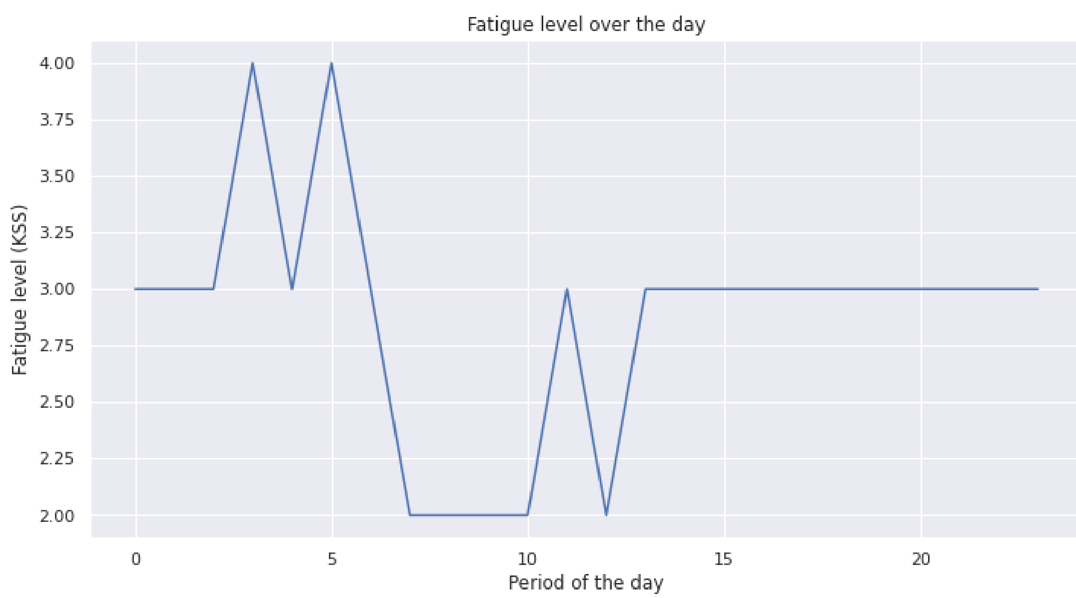

Figure 5.5 Fatigue levels over the day

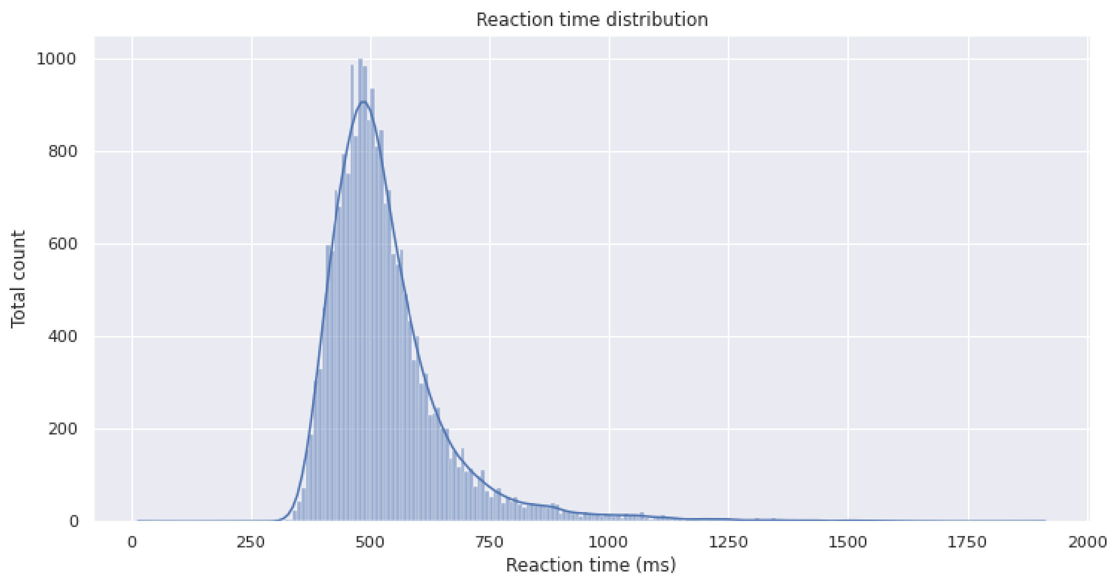

Figure 5.6 Reaction time histogram

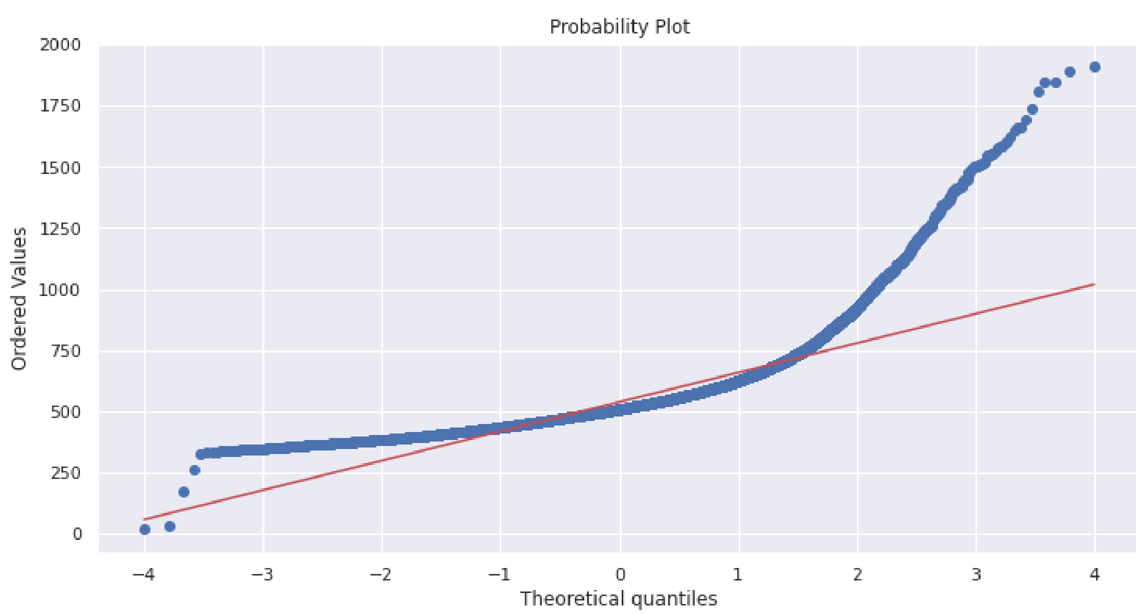

Figure 5.7 Reaction time probability plot

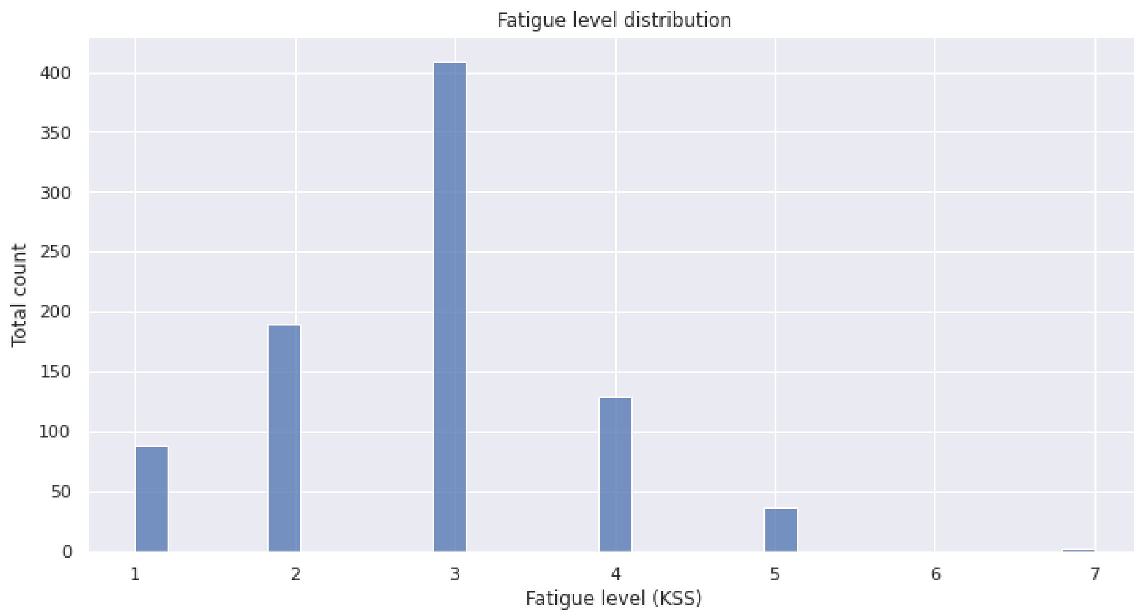

Figure 5.8 Fatigue level histogram

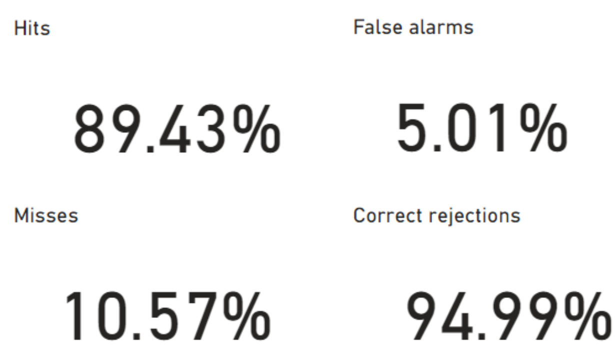

Figure 5.9 SDT results

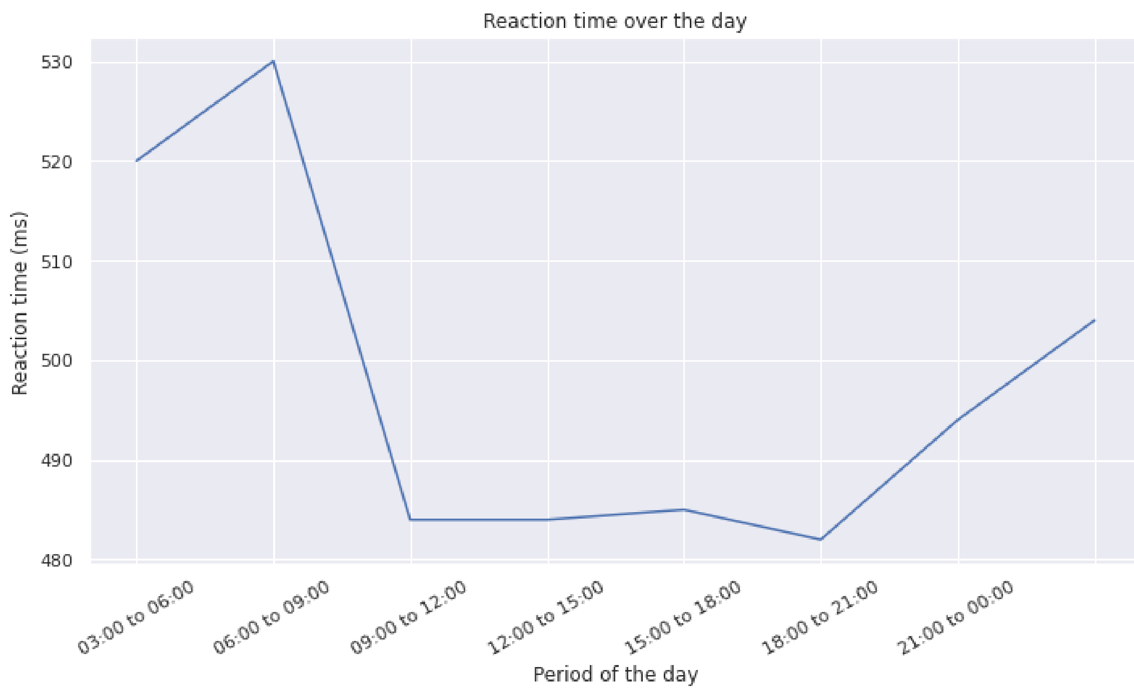

Figure 5.10 Average reaction time aggregated in periods

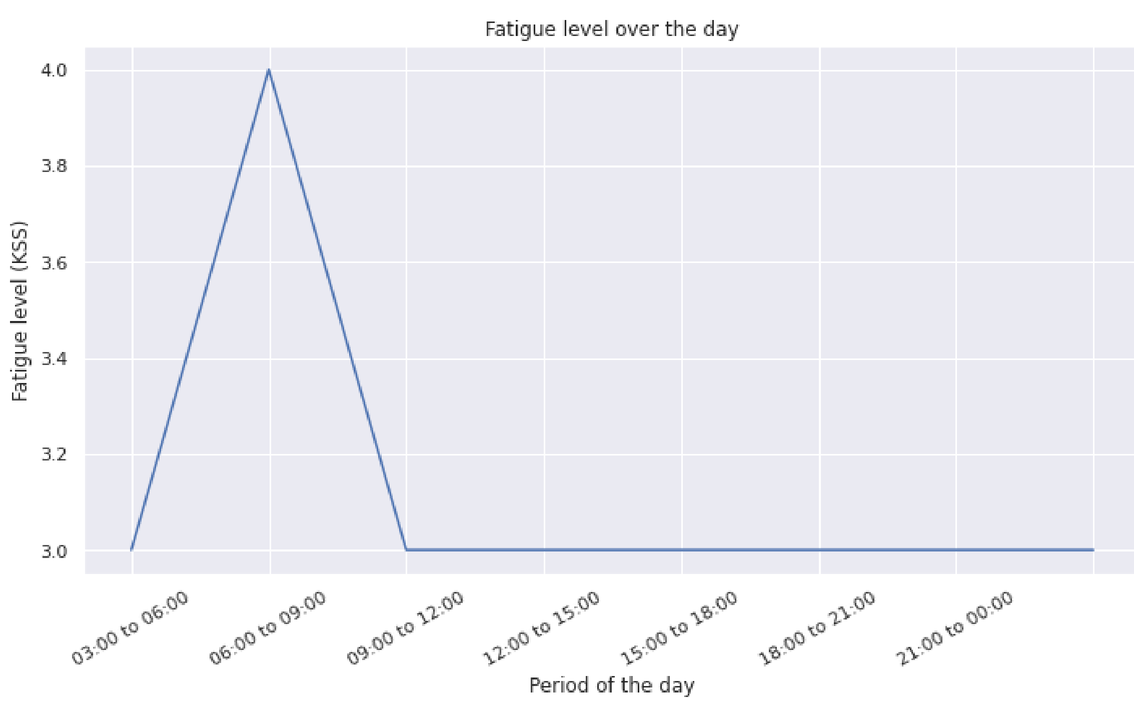

Figure 5.11 Fatigue level over the day

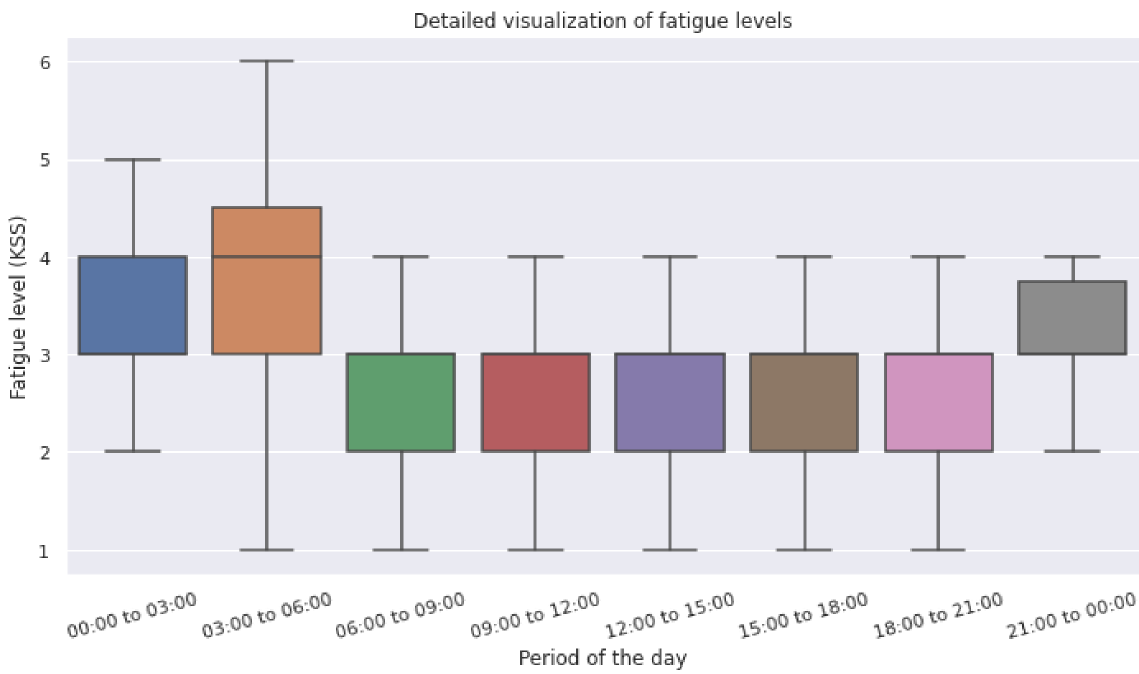

Figure 5.12 Box plot of daily fatigue levels

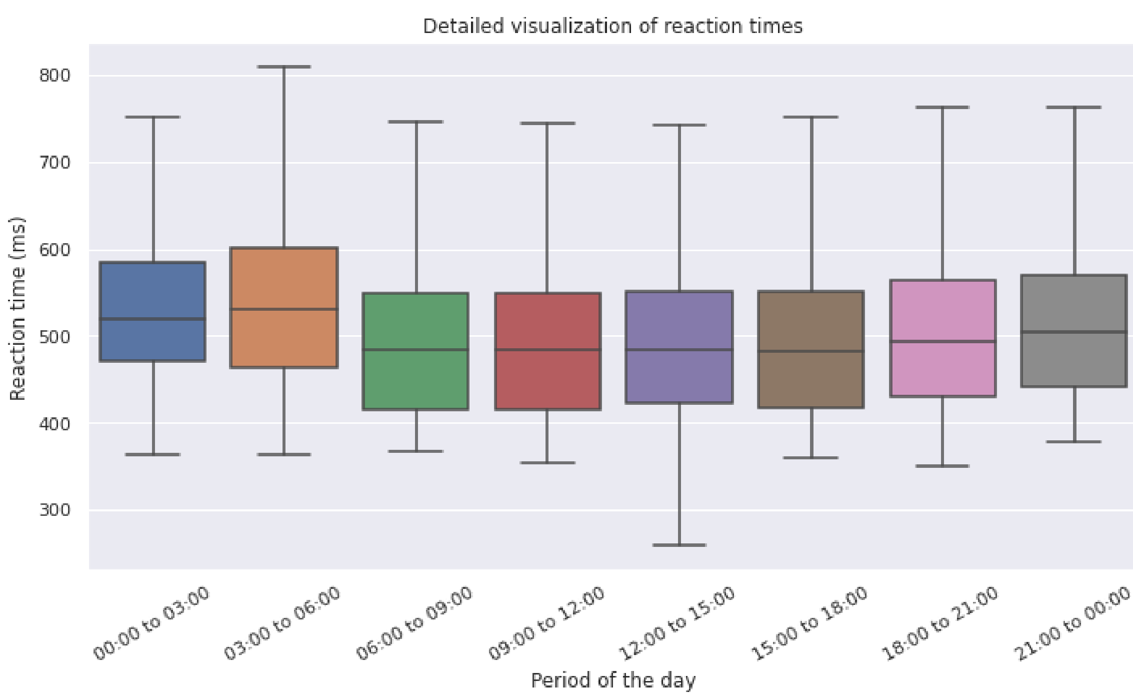

Figure 5.13 Box plot of daily reaction times

Table 5.1 Raw data basic statistics.

Statistics	Value
Mean	451.822313
Standard deviation	240.327297
Minimum	0.000000
25%	432.000000
50%	497.000000
75%	566.000000
Max	1913.000000

Table 5.2 Hourly reaction times percentiles data.

Hour of day	**Percentile**								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	387.2	458.2	483	502	519	543	569	601.6	656
1	0	453	475	497.2	513.5	530	551	585.4	632
2	0	453	486.2	509.6	530	549	577	610.2	682.6
3	412.3	462	492	510.4	535.5	559.6	593	635.8	710.7
4	0	421.8	477	504.2	529	553.8	587.1	625	709.4
5	0	441.8	472.7	501.2	526	546.4	576.3	616	684.7
6	0	0	445.6	478	500	523.2	547.4	578.6	631.6
7	0	0	414.3	443	464	487	515	550	627.8
8	0	394.8	442	464	487	509	531	575	628.6
9	0	392	436	459	482	501	519.6	553	603.8
10	0	368.2	437.6	467	489	506	533.4	569	621
11	0	384.4	427.6	454	482	509.2	540.4	580	661
12	0	410	444.9	466	486	506.8	536.6	584.8	678.6
13	0	73.4	434	463	483	502	527.4	556.8	617.8
14	0	0	434	462	485	510.6	540.6	580.4	666.4
15	0	386.2	440	464	485	505.8	531	577	685
16	0	388.8	436	457	476	499.8	525.1	567.8	643.7
17	0	0	440	466	485.5	510	534	574	635.5
18	391.8	432	452.1	474.6	498.5	528.2	551.9	597	669.2
19	0	0	404.9	445.2	475	496	523.1	566	625.1
20	0	428.8	464.7	485.6	506	529	558.3	587	652
21	0	0	443.8	472.2	495.5	519.8	546.1	586.8	650.7
22	0	435	463	487	505.5	529	555.5	589	659
23	0	403.2	460.9	490.2	511	533	559.1	595	660.7

Table 5.3 Three hours aggregated reaction time percentile data.

Period	**Percentile**								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	0	455	483	503	520	542	569	601	660.5
2	0	445	481	505	530	554	585.5	623	703
3	0	0	436	461	484	508	534	570.6	629.3
4	0	380.2	434	461	484	506	531.8	567	628.8
5	0	385	437	463	485	506	533	574	649
6	0	373.2	438	462	482	505	531	575	652.4
7	0	405.2	445	472	494	518	547	583.8	647.9
8	0	414	455.9	482	504	528	555	589	657.4

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

Considering the questions posed and the objective of this study it we understand that it was able to achieve the desired goals within its limitations. The first point is that the collected data points toward some correlation between fatigue levels and reaction times and these fluctuate throughout the day and between shifts.

The second point relates to the deployment strategy. Even though it was under the initial expectations, it was shown that it can be successful if the proper environment is set and if there is support towards it. A key element is company support and the need for cultural changes both in the workforce and in the organization. To evaluate it a pre and post deployment questionnaire are essential, and it is recommended in future studies.

The final objective relates to off the shelf IoT solutions. It can be said that there are limitations to the capacity of these devices, and they need to be proper considered before deployment in a mine site. On the other hand, they have the capacity to add value to operations and enable fast deployment and the use of already existing and stable data monitoring and collections.

There are limitations to the developed application and more inputs are necessary for better analysis. The verification of integration with existing OHSMS systems is an important question that this study was not able to answer. With this on mind the questions posed still lie: Do test results change throughout an operational day? Do shifts influence test results? Is there any relation between the results from the tests?

Since only two variables were collected and analyzed a correlation analysis was avoided but in general, the trends shown in the results lead to believe that there is at least some relation between the results of the tests. Other than that, it was clear how test results change throughout the day and how there is more fatigue and slower reaction times in night shifts.

The deployment of the tool shows the need of providing adequate training to operators and evidence some of the challenges that exist on deploying technologies in the mining industry. An aspect that was not expected was some of the cultural challenges faced and the difficult to communicate with decision makers in some cases.

Looking at the research objectives defined for the study, the system was able to explore and investigate both reaction times and fatigue within its limitations. The use of IoT as the technology chosen for the research turned out to generate value and provides possibilities to investigate fatigue with the aid of smartwatches via customizable solutions. The advantage of using this kind of technology is that it is constantly evolving, and soon even better sensors will be available for use. Since the application is coded using the manufacturer SDK its portability should be easy to execute.

In terms of recommendations for future research there is still much that needs to be studied when it comes to fatigue. More information on the site work schedule and on the operators would be of great value and would probably enable different analysis and search for patterns on fatigue events. As previously stated, surveys to better understanding the site workforce are essential, a larger pool of people might prove beneficial, and having data from different sites with different policies can point towards how different organizations manage fatigue.

A particular topic/area that the RTFM app can help is as input for bio-mathematical models. Considering that reaction times and subjective sleep levels have shown to follow a trend, they could be inputs for models that try to predict fatigue.

Ultimately, even though some investigation on fatigue was done, the major problem associated with it still lies, how can companies and organizations detect and prevent fatigue events accurately? More investigation should be done, and companies should try to support researchers since fatigue affects employees and organizations as a whole and creates risk in all kinds of manners.

APPENDIX A

JUPYTER NOTEBOOK

```
# -*- coding: utf-8 -*-
"""thesis_data.ipynb

Automatically generated by Colaboratory.

Original file is located at

https://colab.research.google.com/drive/1ZIayW71ieIg0mSMXhWCv5xBQ2QELanO
8
"""

import seaborn as sns
import pandas as pd
from matplotlib import pyplot
from datetime import datetime

a4_dims = (11.7, 6)

reaction_data = pd.read_excel("/content/reaction_data.xlsx")
fatigue_data = pd.read_excel("/content/fatigue_data.xlsx")
identifier = pd.read_excel("/content/identifier.xlsx")

reaction_data = reaction_data.merge(identifier,  left_on='fitbit_id',
right_on='id')
fatigue_data = fatigue_data.merge(identifier, left_on='fitbit_id',
right_on='id')

reaction_data['weekday'] = reaction_data['date'].dt.weekday
fatigue_data['weekday'] = fatigue_data['date'].dt.weekday

reaction_data

sns.set_theme()

reaction_daily_period =
reaction_data[(reaction_data['company']=='northcomplex')
                        &
(reaction_data['state']==1)].groupby(['dailyperiod']).median()
fatigue_daily_period =
fatigue_data[(fatigue_data['company']=='northcomplex')]
                        .groupby(['dailyperiod']).median()
```

```
reaction_daily_hour =
reaction_data[(reaction_data['company']=='northcomplex')
                        &
(reaction_data['state']==1)].groupby(['hour']).median()
fatigue_daily_hour =
fatigue_data[(fatigue_data['company']=='northcomplex')]
                    .groupby(['hour']).median()

reaction_daily_period

fig, ax = pyplot.subplots(figsize=(11.7, 6))
ax = sns.lineplot(x="hour", y="reaction_time",
data=reaction_daily_hour)
ax.set_xlabel("Period of the day")
ax.set_ylabel("Reaction time (ms)")
ax.set_title("Reaction time over the day")

fig.show()
fig.savefig("reaction_period")

fig, ax = pyplot.subplots(figsize=(11.7, 6))
ax = sns.lineplot(x="dailyperiod", y="reaction_time",
data=reaction_daily_period)
ax.set_xticklabels(labels = ["00:00 to 03:00", "03:00 to 06:00"  ,
"06:00 to 09:00", "09:00 to 12:00",
                             "12:00 to 15:00", "15:00 to 18:00", "18:00
to 21:00",  "21:00 to 00:00"]
                   ,rotation=30)
ax.set_xlabel("Period of the day")
ax.set_ylabel("Reaction time (ms)")
ax.set_title("Reaction time over the day")

fig.show()
fig.savefig("reaction_period")

fig, ax = pyplot.subplots(figsize=(11.7, 6))
ax = sns.lineplot(x="hour", y="fatigue_level", data=fatigue_daily_hour)

ax.set_xlabel("Period of the day")
ax.set_ylabel("Fatigue level (KSS)")
ax.set_title("Fatigue level over the day")

fig.show()

fig, ax = pyplot.subplots(figsize=(11.7, 6))
ax = sns.lineplot(x="dailyperiod", y="fatigue_level",
data=fatigue_daily_period)
ax.set_xticklabels(labels = ["00:00 to 03:00", "03:00 to 06:00"  ,
"06:00 to 09:00", "09:00 to 12:00", "12:00 to 15:00", "15:00 to 18:00",
"18:00 to 21:00",  "21:00 to 00:00"],rotation=30)
ax.set_xlabel("Period of the day")
ax.set_ylabel("Fatigue level (KSS)")
ax.set_title("Fatigue level over the day")

fig.show()
fig.savefig("reaction_period")
```

```
fig, ax = pyplot.subplots(figsize=a4_dims)
ax = sns.boxplot(x="weekday", y="reaction_time",
    data=reaction_data[(reaction_data['company']=='northcomplex')
    & (reaction_data['state']==1)], showfliers=False)

fig.show()

reaction_data[(reaction_data['company']=='northcomplex')
& (reaction_data['state']==1)].pivot(columns='hour',
values='reaction_time')

percentiles = reaction_data[(reaction_data['company']=='northcomplex')
& (reaction_data['state']==1)].pivot(columns='hour',
values='reaction_time').quantile([0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6,
0.7, 0.8, 0.9])

type(percentiles)

daily_period = reaction_data[(reaction_data['company']=='northcomplex')
&
(reaction_data['state']==1)].pivot(columns='dailyperiod',values='reacti
on_time') quantile([0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9])

reaction_data['reaction_time'][(reaction_data['company']=='northcomplex
')
& (reaction_data['state']==1)].describe()

reaction_daily_period[(reaction_daily_period['company']=='northcomplex'
)
& (reaction_daily_period['state']==1)].pivot(columns='dailyperiod',
values='reaction_time')

percentiles.to_csv("percentiles.csv")

fig, ax = pyplot.subplots(figsize=a4_dims)
ax = sns.boxplot(x="dailyperiod", y="reaction_time",
        data=reaction_data[(reaction_data['company']=='northcomplex') &
(reaction_data['state']==1)], showfliers=False)
ax.set_xticklabels(labels = ["00:00 to 03:00", "03:00 to 06:00"  ,
"06:00 to 09:00", "09:00 to 12:00", "12:00 to 15:00", "15:00 to 18:00",
"18:00 to 21:00",  "21:00 to 00:00"]
                   ,rotation=30)

ax.set_xlabel("Period of the day")
ax.set_ylabel("Reaction time (ms)")
ax.set_title("Detailed visualization of reaction times")

fig.show()

fig, ax = pyplot.subplots(figsize=(11.7,6))
ax = sns.boxplot(x="dailyperiod", y="fatigue_level",
data=fatigue_data[(fatigue_data['company']=='northcomplex')],
showfliers=False)
ax.set_xticklabels(labels = ["00:00 to 03:00", "03:00 to 06:00" ,"06:00
to 09:00",09:00 to 12:00", "12:00 to 15:00", "15:00 to 18:00",
"18:00 to 21:00",  "21:00 to 00:00"]
                   ,rotation=15)
```

```
ax.set_xlabel("Period of the day")
ax.set_ylabel("Fatigue level (KSS)")
ax.set_title("Detailed visualization of fatigue levels")

fig.show()

fig, ax = pyplot.subplots(figsize=a4_dims)
ax = sns.boxplot(x="weekday", y="fatigue_level",
data=fatigue_data[(fatigue_data['company']=='northcomplex')],
showfliers=False)

fig.show()

fig, ax = pyplot.subplots(figsize=(12,6))
ax = sns.histplot(data=reaction_data[(reaction_data['state']==1) &
(reaction_data['reaction_time'] != 0)], x='reaction_time', kde=True)

ax.set_xlabel("Reaction time (ms)")
ax.set_ylabel("Total count")
ax.set_title("Reaction time distribution")

fig.show()

fig, ax = pyplot.subplots(figsize=(12,6))
ax = sns.histplot(data=fatigue_data[fatigue_data['company'] ==
'northcomplex'], x='fatigue_level')

ax.set_xlabel("Fatigue level (KSS)")
ax.set_ylabel("Total count")
ax.set_title("Fatigue level distribution")

fig.show()
```

APPENDIX B

TRAINING MATERIALS

Fatigue Management

Instructions:

- Open the RTFM app on your smartwatch at the beginning of the shift.
- Do the fatigue and reaction assessment when prompted, as instructed below. Make sure that it is safe to do the assessment. ONLY do it when you are stopped. The app will remind you periodically until the assessment is done.
- The assessment will repeat itself throughout the shift. You will be prompted once every two hours.
- After a certain time or number of assessments the application will stop.

Fatigue Scale

1—Extremely Alert

2—Very Alert

3—Alert

4—Rather alert

5—Neither alert nor sleepy

6— Some signs of sleepiness

7—Sleepy, but no effort to keep awake

8—Sleepy, but some effort to keep awake

9—Very sleepy, great effort to keep awake, fighting sleep

10—Extremely sleepy, can't keep awake

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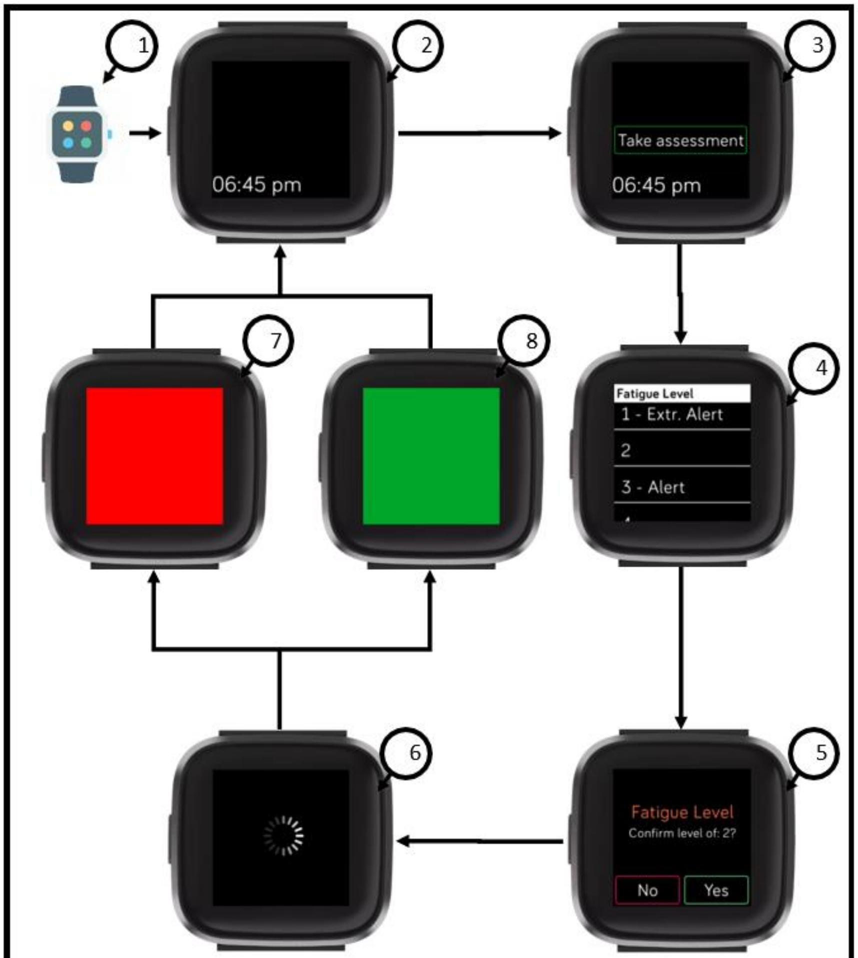
Figure B.1 Page 1 of user RTFM training material



1—Open FM app at beginning of shift	5—Confirm fatigue level
2—Main screen with time	6—Wait for reaction test
3—Assessment screen: Click when ready	7— If screen is red, DO NOT respond (no click)
4—Select your fatigue level from 1 to 10	8—If screen is green, CLICK screen as fast as possible

Figure B.2 Page 2 of user RTFM training material

Instructions for RTFM app installation and use

1. Please download the Fitbit app to your cell phone (if you have not already)

Android phones: https://play.google.com/store/apps/details?id=com.fitbit.FitbitMobile&hl=en_US

iPhones: https://apps.apple.com/us/app/fitbit-health-fitness/id462638897

Set up your Fitbit user account (https://www.fitbit.com/), following instructions provided by Fitbit.

2. Install the RTFM app by clicking on the link below and following the instructions. http://app.umodelfatigue.com/install
3. Go to the authentication webpage: http://app.umodelfatigue.com/c/rio

   This webpage will use your Research ID (INITIALS + birth date (e.g., **Joe Smith** born **04/08/65** = **JS040865**) and create a unique Fitbit User ID. First enter the Research ID in both fields, then click on the AUTHENTICATE button. The Research ID is identical to the one you used on the fatigue survey.
4. After being redirected to the Fitbit homepage login with your Fitbit account.
5. You will receive a unique User ID on the webpage. Please enter this unique User ID into your Fitbit app on your smart phone. Detailed instructions are provided on the webpage.

Once you have completed these steps, you are all set. For detailed video instructions please follow the link below:

https://www.youtube.com/watch?v=VQd4nm6hVVI&ab_channel=Jo%C3%A3oMarques

Important: Please remember to **start your FM app** on your Fitbit every time you are **on the shuttle** to the mine (from your Fitbit main screen swipe left until you see the icon, then click on it). This way we will collect the data while you are at work. The app stops automatically after 12 ½ hours, so at the end of your work you do not need to do anything. However, if you need to stop the app for some reason, you can click the Fitbit button twice which will terminate the app immediately. Also, remember your safety is critical, so if you are prompted by the app (vibration) to enter your fatigue level, wait until you arrive at a place where you can stop the vehicle. ONLY THEN enter your fatigue level and complete the reaction time assessment.

Finally, the Fitbit will need to be charged every 2-3 days. Please make sure that you recharge it.

Please **contact us** if you have any questions:

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João Marques	joao.desousamarques@utah.edu	Cell: 425 480 9137

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