Msc Integrated Product Design

FINAL THESIS

Increasing Empathy Towards Gig Workers Through Communicating Heart Rate Data

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15/08/2022

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Abstract

This thesis demonstrates that there is a need for improving the working conditions of gig-workers. It establishes a need for an increase in empathy from consumers towards delivery riders. Delivery riders often make use of E-bikes which provide an excellent foundation for data collection. The main research question is stated as follows:

How can empathy towards delivery riders be increased through communicating behavioural data to the consumer?

After establishing background and related work through desktop research, an exploration into the implementation of multiple sensors was initiated. This led to the insight that communicating heart rate data is the most promising dataflow to evoke empathy. The effect of communicating live heart rate data, next to static personalised information was empirically tested. After which all insights were synthesized into 5 design drivers which provided input for a brief design cycle. The final output is a demonstration, including a prototype, of a proof of principle that evokes empathy through communicating live heart rate data.

The most important insight substantiated in this thesis is the positive correlation that communicating live heart rate data has to the experienced empathy from end-consumers towards delivery riders. This lead to the final proof of principle that revolves around a way to implement this into the delivery service context.

The conclusion of this study is that there is a strong indication that showing live heart rate data to consumers increases the experienced empathy. This could be implemented in various ways and provides a foundation for future work. More research is needed to establish the exact origin for the increase in empathy. This study is limited to exploring one way of communicating live heart rate data so more research is needed on different possibilities regarding visualization, communication and information versus the effect on experienced empathy.

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1. Introduction

1.1 Analogy

It's a regular Friday evening, you decide to celebrate the weekend and go out for dinner. Over the course of the evening, you order food, and a waiter is delivering this food to your table. The interactions between the consumer and the waiter are minor but after dinner you thoughtfully thank him for the service this evening and give a tip for his efforts. Two days later, on Sunday, it is pouring rain and you decide to stay in. Making use of a platform-based delivery service, the consumer is able to order food within 4 clicks on the designated app. A delivery person rides his bicycle for 10 minutes during the rain, when he arrives you briefly thank him and quickly go to your kitchen to grab cutlery and enjoy your meal. After you've finished you come to realise, why was I thanking the waiter extensively, but did I not appreciate the soaked biker 30 minutes ago as much as he deserved?

There seems to be a discrepancy between the appreciation consumers have for more old-fashioned services and servants within the rising platform-based gig economy.

1.2 Problem Definition

In this thesis, I seek ways to bridge the gap between workers and consumers in this gig economy, focusing on the lack of empathy between them. The goal is to increase the level of empathy towards delivery riders at the consumers' front door. This will be done through better visualizing the working conditions and effort of the workers. This visualization can be best realised through collecting behavioural data, which is defined as observational information collected about the actions and activities of an animal or human. In literature it is proposed that communicating behavioural data evokes empathy (see Chapter 2.3.2, Background & Related Work/Static vs Dynamic Data/Dynamic). This collection of behavioural data will mostly be done through biosensing, trying to capture the physical state of the gig worker. The main research question is formulated as follows:

> *RQ = How can empathy towards delivery riders be increased through communicating behavioural data to the consumer?*

First, the context of the project that was established will be elaborated. This will further define the problem, scope and relevant terms in this domain and create an overview of the relevant circumstances that were a foundation for the research.

1.3 Context

In recent years, a new means of transportation has been becoming a more and more common sight on European streets. The market for electric bicycles (e-bikes) is booming at double digit annual growth rates (Toll, 2021). Unlike regular bikes, e-bikes require additional user interfaces for the selection of individual motor support levels and for controlling of the battery status. These interfaces are typically implemented as small devices mounted on the handlebars and often additionally provide basic information about the speed and mileage of the e-bike. Recently, some producers have started to integrate more comprehensive features into these e-bike computers, such as navigation functionality, fitness applications and smartphone connections, and to provide data-based services to the e-bike users. The idea of collecting and displaying data about bicycle usage is not new. Cyclometers as well as a range of smartphone applications have been offering functionality for tracking and displaying bicycle routes for years (Flüchter & Wortmann, Mobile sensors on electric bicycles, 2014). As the e-bike market is maturing, the collection, analysis and display of usage data is becoming an important source of differentiation for competitors (Flüchter & Wortmann, Implementing the connected e-bike: challenges and requirements of an IoT application for urban transportation, 2014).

The sale of electrically assisted bicycles (e-bikes or pedelecs) is growing at a rapid rate across Europe. Within Europe, the Netherlands is one of the biggest markets for e-bike sales with 10.4 sales per 10,000 people, roughly equating to 17 per cent of all Dutch bicycle sales. Around 1 million e-bikes are now in ownership out of a total stock of 22 million bicycles for 17 million Dutch inhabitants (Kroesen & Harms, 2018). Due to their advantages over traditional bicycles in terms of e.g., reach, effort and independence from local topography, e-bikes may be able to qualify as important element of future transportation systems, eventually replacing automobiles not only on leisure trips but also for commuting to work. (Flüchter & Wortmann, Mobile sensors on electric bicycles, 2014). The courier and parcel service provider segment is notably responsible for growth in e-mobility transportation. The industry is expected to contribute a worldwide maximum revenue share of more than 45% by 2031 (FMI, 2022).

1.4 Enabling data collection

There is a relatively high interest of users in the e-bike data, which is accompanied with high expectations regarding data quality and visualization, that appear to be driven by existing smartphone applications, which are setting standards in the sports and fitness environment. The willingness of users to share their e-bike sensor data with the e-bike manufacturer appears generally high. E-bikes provide an excellent setting for implementing state of the art sensors and novel computing systems since e-bikes have an integrated power supply which provides the possibility to implement almost all mobile sensors (Flüchter & Wortmann, Implementing the connected e-bike: challenges and requirements of an IoT application for urban transportation, 2014).

1.5 Gig Work

The proliferation of new and increasingly diverse digital labour platforms is one of the major economic developments of recent years (Healy, Pekarek, & Vromen, 2020). This platform labour economy has generated opportunities for flexible work and business innovation, but it has also created significant economic, social, and personal challenges for so called Gig Workers. Gig workers are defined as 'people who enter into formal agreements with on-demand companies to provide services to the company's clients' (Donovan, Bradley, & Shimabukuro, 2016). Within analysis of 28 papers, gig work is described to be short term (73.08%), requires the completion of finite assignments (84.62%), and allows loose boundaries for when and where people must work (80.77%) (Watson, Kistler, Graham, & Sinclair, 2021). These characteristics have resulted in gig work being precarious. Meaning it is often low paid, temporary, provides no health, training, or retirement benefits, and shifts more of the risk of doing business from the employer to the contractor (Bajwa, Knorr, Ruggiero, Gastaldo, & Zendel, 2018). Gig work is seen as insecure and exploitative by many labour and organizational scholars (Stanford, 2017), (Doorn, 2017), (Aroles, Mitev, & Vaujany, 2019). As the gig economy grows and matures, platforms will face further demands, not only to comply with current employment laws, but also to adopt sustainable labour practices that treat workers as integral, rather than incidental, to business goals (Healy, Pekarek, & Vromen, 2020). Personally, when applying for a gig job myself, I was surprised by the fact that the second question (after my full name) to answer in their online application portal was *"Do you have a social security number?"*. Followed by a list of six different options on how you were able to apply without a social security number. This illustrated how employers are targeting people without a lot of different job opportunities as applicants for their work. Articles from reporters that went undercover illustrate this image and described the employee base as very limited "lost" native students, but mostly foreigners and undocumented immigrants (Bergeijk, 2021). It resonates with a stereotypical view of delivery riders, which are often immigrants that have a poor local linguistic expertise (and perhaps no social security number).

1.6 Employers

The employers of Gig Workers in the delivery segment have a reputation of extraordinary harsh contracts. The Dutch Labour Inspectorate ascertains relatively many violations by rapid delivery companies in both working circumstances and employment contracts (Nederlandse Arbeidsinspectie, 2022). According to Saskia (54) the contracts are a stranglehold for employees pointing to the non-competition clause at one of the rapid grocery delivery services that prohibit employees to work for competitors at fines of €1000,- per violation and another €500,- per day (Lommen, 2022). Such severe non-competition clauses are directly opposing the beneficial definition of Gig Work in which workers enjoy freedom to execute a few 'gigs' when desired. Personally, I solicited at another rapid grocery delivery service and encountered the following confidentiality clause in the contract:

"7. Confidentiality

It is forbidden for the Employee, both during the Employment Agreement and after its expiry, in any way whatsoever, to disclose to third parties, directly or indirectly, in any form and in any sense whatsoever, any particulars of or concerning which he/she has obtained knowledge in the performance of his/her duties in connection with the business and interests of the Employer and of undertakings allied with the Employer."

The clause preventing me from reporting any findings during employment could not be bypassed upon request and thus forestalled me in gaining hands-on experience in context. It underscores the impression that these companies are like black boxes and want to share as little information as possible trying to disguise what is happening inside.

1.7 The gap between gig workers and society

Journalist Jeroen van Bergeijk went undercover at a platform-based service provider for rapid grocery delivery. After three weeks, the image that lingers with him is of a generation divided into two worlds, with one millennial serving the other. Two scenarios in which one millennial must settle for an undemanding flex job and will never be able to buy a downtown condo. And who should allow the other successful, wealthy millennials to live comfortably.

Where once only the wealthy could afford staff, owing to the digital economy and venture capitalists, the middle class can now do so as well — but without noblesse oblige (Bergeijk, 2021).

At the same time, platform companies seek to acquire a new form of power, by cultivating the loyalty and, occasionally, more active support, of consumers for whom platform services constitute 'part of the infrastructure of their lives' (Culpepper & Thelen, 2019). These corporations focus on raking in the support of the consumer while they are neglecting the needs of their workers, driving a wedge between societal groups. Next to the described ruthless treatment from employers, reporters and riders also describe a lot of unsympathetic treatment from customers. Experiencing degrading comments after they had to climb multiple floors to deliver one 500ML cup of ice cream.

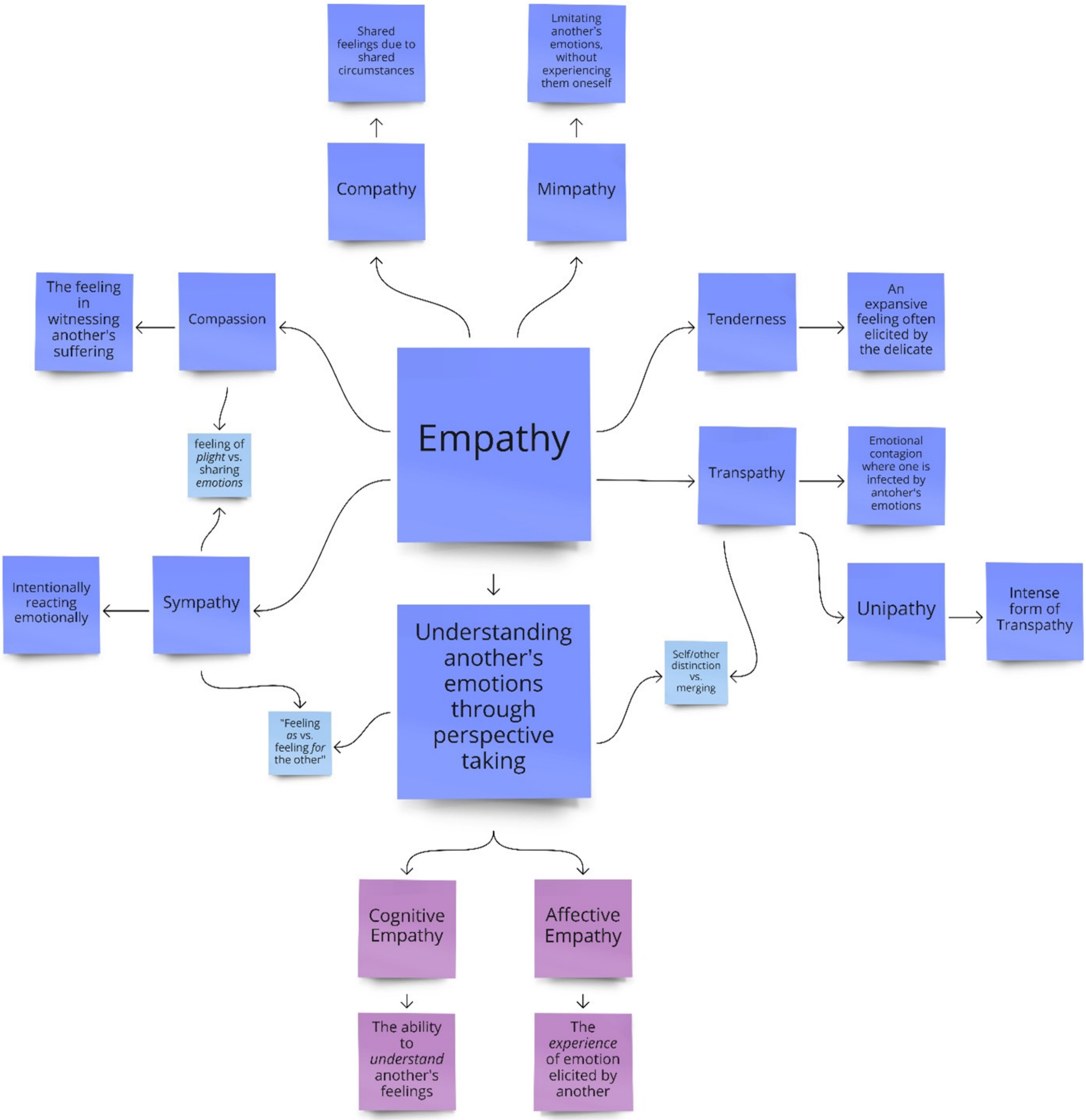

Figure 1, Concepts related to empathy

2. Background & Related Work

A brief introduction to different aspects of the context for this project has been stated in the chapter above. In order to take a deeper dive into the most important definitions and aspects, more foundational research was done on the following topics: the definition of empathy, (bio-)sensors and static vs dynamic data.

2.1 Definition of empathy

Empathy is defined as "understanding another's emotions through perspective-taking" (Cuff, Brown, Taylor, & Howat, 2016). In this research, empathy is described in the context from a consumer towards an individual delivery rider.

Empathy is a form of connectedness between two people that can be elicited or enhanced by environmental stimuli. There are many differences in the way researchers and practitioners conceptualize empathy (Mann & Barnett, 2012). Empathy is considered to consist of cognitive empathy and affective empathy, however due to extensive interaction, separation of the two concepts has been rejected (Cuff, Brown, Taylor, & Howat, 2016). Empathy is also often closely related, but not the same as, sympathy or compassion. The main differences being that empathy is defined as taking over another's emotion whilst the feeling of sympathy recognizes another's emotion. For example, if someone is feeling sad empathy will cause the observer to feel sad as well, sympathy will rather cause feelings of concern for another. Compassion is considered a higher construct consisting of feelings of sympathy and pity. Compassion is more related towards feeling for another's plight instead of sharing the same emotion (Batson, 2009).

Similar or related concepts to empathy have been defined and mapped in Figure 1 empathy similar concepts. Where definitions are overlapping or connected, a distinction has been added in the form of a brief statement (Batson, 2009). For this study, it is acknowledged that there will be overlap between terms, but the focus will lie on evoking empathy defined as "understanding another's emotions through perspective-taking".

Figure 2, Sensor exploration

2.2 Sensors

As mentioned in chapter 1.2 Introduction/Problem Definition, the aim is to increase the previously defined experience of empathy through behavioural data. Data has to be captured by sensors before being able to communicate it. An explorative overview was created including the main relevant sensors that are currently available off-the-shelf. They have been clustered into overarching sensor areas: environmental -, mechanical -, geological - and biosensors. As mentioned in the introduction, literature suggests that E-bikes provide a good foundation for sensor implementation mainly due to the available power supply through the integrated battery. The biggest challenge lies in the biosensors as most of them have to be within direct contact of the subject (wearables) and cannot be connected to the internal power supply or implemented in the frame. However, these also seem most promising with regards to evoking empathy (Liu, Kaufman, & Dabbish, The Effect of Expressive Biosignals on Empathy and Closeness for a Stigmatized Group Member, 2019) and are therefore essential for this study in order to answer RQ1 (see, chapter Introduction).

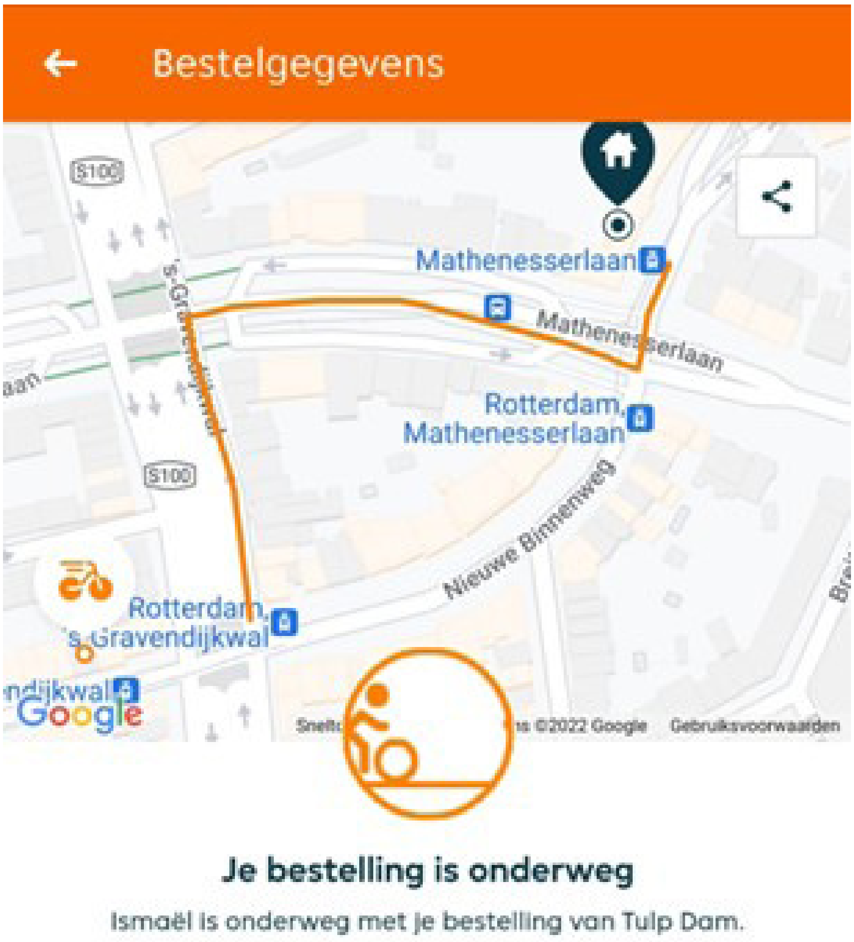

Figure 3, personalization from Thuisbezorgd

2.3 Static vs dynamic Data

There are two main differences regarding datasets. Static and dynamic data. The differences in collection, communication and opportunities are described below.

2.3.1 Static

The entire business paradigm shifts from mass-produced goods and standardized services to an emphasis on personalized one-to-one contact (Fan & Poole, 2006).

According to Apurva Dalal, Head of Engineering for Uber India; "With the introduction of Driver Profiles, driver partners can personalize an informative profile to share with riders that spark awesome conversations and experiences. We believe it will have a positive impact on furthering trust and empathy between riders and driver partners," (Vijayasarathy, 2017).

This resonates with more of state-of-the-art platform-based service providers. For example, Thuisbezorgd recently implemented the name of the delivery driver to their food tracker (see figure 3, personalization from Thuisbezorgd).

2.3.2 Dynamic

Since the nature of biosignals is always dynamic opposed to static information, it is referred to as dynamic data in the context of this research. Literature has explored the effect of biosignals on evoking empathy. People can infer someone else's psychological state from their biosignals, and subsequently feel more aware of them (Liu, Expressive Biosignals: Authentic Social Cues for Social Connection, 2019). According to (Curran, Gordon, Lin, Sridhar, & Chuang, 2019), biosensory information triggers the mind into experiencing an increased feeling of empathy (validated through virtual reality video stimuli). Since empathy can also be evoked by a fictional or imaginary person (Decety & Jackson, 2004), (Pelligra, 2011), (Singer & Lamm, 2009), and there is little functional difference between empathy for a real, fictional, or absent person (Cuff, Brown, Taylor, & Howat, 2016) and simulations are not limited to measuring the minimum, but in fact are rich opportunities to assess behavioural empathy in detail (Teherani, Hauer, & O'Sullivan, 2008) the use of dynamic biosensory data should evoke empathy.

3. Research Questions & Hypotheses

The Research Question was stated as follows:

> *RQ = How can empathy towards delivery riders be increased through communicating behavioural data to the consumer?*

With the accompanying hypothesis of:

> *H = By communicating behavioural data to the consumer we can increase empathy towards the delivery rider.*

To appropriately answer this research question, the research has to be divided into two parts. First, the focus will lie on answering RQ2 to test feasibility of sensors and gain actual understanding of sensors in context. This is mainly done through exploration and tinkering with the implementation of sensors through prototyping. The results can be found in chapter I - Results. Research Question 2 is stated as follows:

> *RQ2 = What (bio)sensors are suitable for implementation within E-bike context in order to provide (behavioural) data flows?*

After defining what sensors would be feasible to implement, how they would be connected and how accurate they are, the second part will focus on the actual evoking of empathy using the generated data. In the research stated above, two different classes of data are distinguished: static and dynamic data. Therefore, this phase is looking at both options, with the accompanying research questions:

> *RQ2.1 = How (significantly) does showing static personalized data to the consumer influence experienced empathy towards a delivery rider?*

> *RQ2.2 = How (significantly) does showing live biosignal data to the consumer influence experienced empathy towards a delivery rider?*

These Research Questions will be answered through empirical quantitative research using a mock-up of a delivery service. The method, results and findings can be found in Chapter II. After answering these research questions, the findings and conclusions of both phases will be combined into one synthesis which can be found in Chapter Conceptualization.

4. Part I - Objectives & Method

In order to generate insights regarding the feasibility of collecting, storing, sending, and visualising data from dedicated sensors, an explorative prototyping phase was initiated. The goal of this phase is answering the previously stated research question:

> *RQ2 = What (bio)sensors are suitable for implementation within E-bike context in order to provide (behavioural) data flows?*

The two factors that were considered most were ease of implementation and to what extent they add to defining the context when deciding which sensors to use. By prototyping the actual sensors within the e-bike, the following have been validated to be easy to implement: microphone, camera, ambient light, torque, accelerometer (XYZ), gyroscope (XYZ), speed, tachometer (cadence), galvanic skin response, RR interval, heart rate, GPS and altimeter. All of these sensors can be combined with a Unix timestamp to synchronise the data flows. To validate which sensors are most efficient more research and testing has to be done.

All findings are described below, finishing this phase with the conclusions as input for the final synthesis which can be found in Chapter 6.1, Synthesis/Design Drivers.

4.1.1 Objective

The stated research question is broadly formulated in order to keep this phase as explorative as possible. However, the objective is to capture data in a useful way instead of wildly collecting different numbers. As discussed in Chapter 4, Part I, Objectives & Method, it is clear what relevant sensors are available. It was concluded that the focus should lie on dynamic data since it is more promising with regards to evoking empathy. On the other hand, static data is inherently easier to generate, collect and communicate as it does not change. The approach for this phase was therefore, using the sensor exploration as foundation, to implement all the sensors that are feasible in order to generate a live overview that describes the context as accurate as possible. It would be preferred to be able to measure the emotional state of the user in order to understand the context and wellbeing of the rider better.

4.1.2 COBI

It was established early on that an e-bike itself is a sensory device. Meaning it has multiple sensors and data streams that could be leveraged by tapping into the controller without the need to duplicate sensors. If feasible, this provides a foundation for a quick gathering of multiple interesting data inputs with minimal necessities. Therefore, this was the first focus for prototyping. Bosch provides a system that uses a smartphone with accompanying COBI.bike app to control e-bikes that make use of a Bosch motor. Within the COBI.bike application it is possible to develop your own module using their Software Developer Kit (SDK) (GmbH, 2022). In order to collect and export mechanical data from the motor such as cadence, speed and user power, a dedicated Angular webapp was created as module within the COBI.bike app. This module was designed to subscribe to the different data flows between the motor and the controller. Also, to make pinpointing interesting events during rides easier the standard equipped thumb controller was adjusted to create an 'event logger'. When pressing the SELECT button on the standard thumb controller, the particular event (point in time) was logged to make analysis more efficient. After subscribing to the data flows, the application sends it to a dedicated cloud application created for Data-Centric Design processes called Bucket (Lab, 2022). Bucket has a Grafana, an open source visualization tool, integration to visualize the data on an easy to configure dashboard. Within Grafana it is possible to set the refresh interval to 5 seconds to establish a nearly live overview. To review the code of the webapp refer to Appendix E, COBI code. To review the open source code of Bucket refer to https://github.com/datacentricdesign/bucket. To review the Angular webapp refer to https://datacentricdesign.github.io/cobi-app.

Figure 4, COBI.bike SDK (Bosch.com)

4.1.3 Biosensors

As concluded in Chapter 2.3.2, Background & Related Work/Static vs Dynamic Data/Dynamic, there was a higher potential for biosignals to evoke empathy. Therefore the next objective was to include biosensors into the live dashboard. Implementation of the biosensors proved a bit more difficult since there is in almost every case the requirement of direct contact with the subject. Due to time constraints, it was decided to focus on two biosignals. The most important and obvious biosignal is the heart rate of the vrider. This could be easily implemented by making use of an Apple Watch, which could be connected to the iPhone. The COBI.bike app provided an integration for extracting heart rate data from fitness apps on the iPhone. Making use of the same architecture as the mechanical data, the heart rate was added to Bucket and followed mostly the same protocols (see Figure 9, architecture) to be visualised in Grafana.

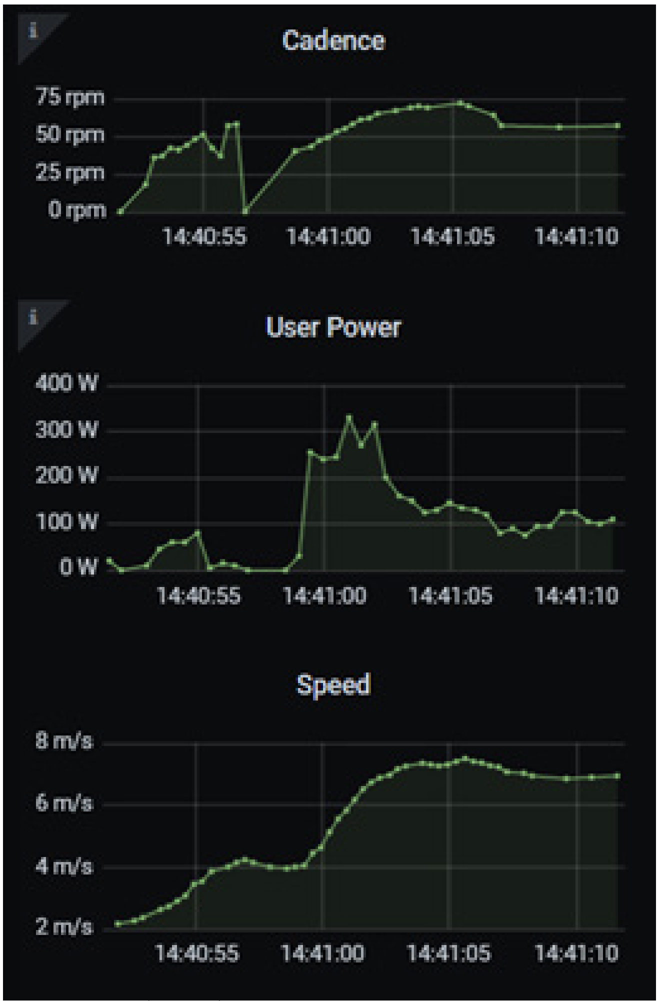

Figure 5, mechanical sensor overview

Figure 7, QR code Grafana

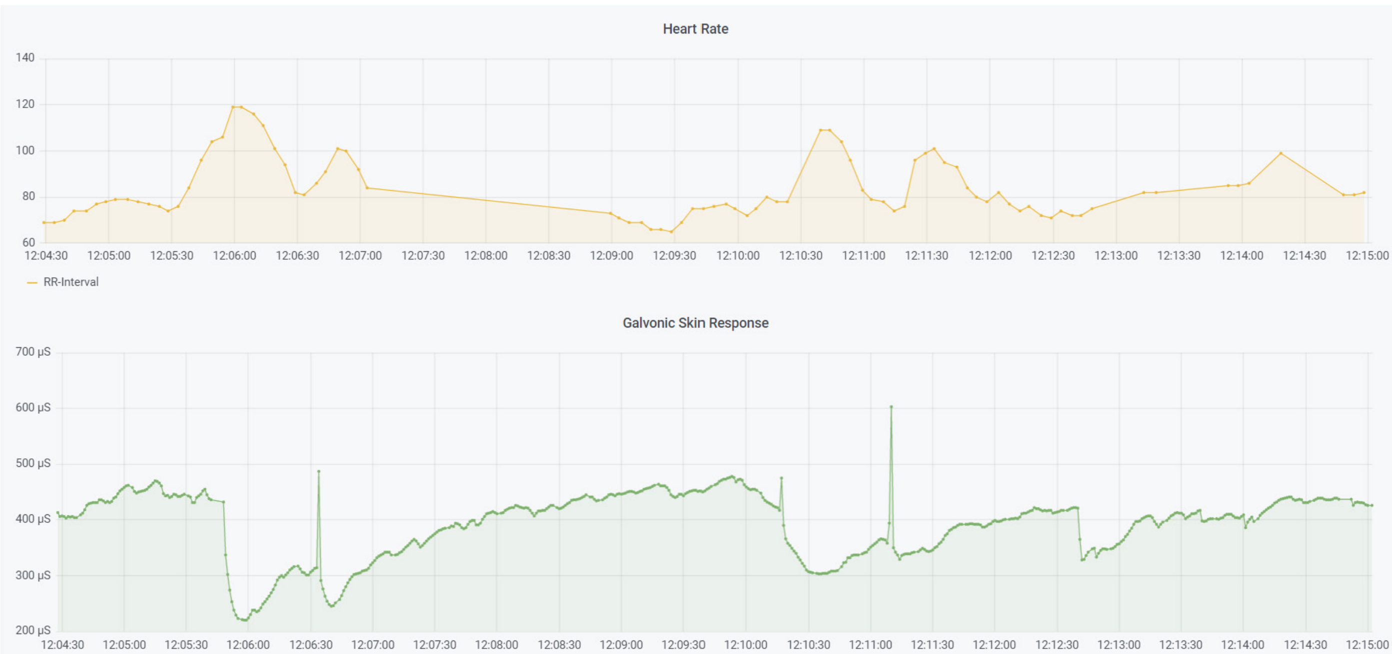

Figure 6, Biosensory Data

4.2 Results

As mentioned, the results could be easily visualised using Grafana Dashboard. Setting the refresh interval to 5 seconds provided a close to live overview of all query's when someone was using the E-bike. A few basic adjustments were made to the panels to increase its clarity such as adding points and units. The final interactive dashboard can be found by scanning the QR code (figure 7, QR code Grafana). For an overview of the graphical representation for cadence (RPM), user power (watts) and speed (m/s) refer to Figure 5, mechanical sensor overview.

The collected data accurately represents the real events. For example, the speed was checked using another GPS device and matched the collected results. It can be expected that if Cadence is (close to) zero, the User Power will also be zero. Also, if User Power drops, Speed will decrease. All is the case as can be seen in Figure 5, mechanical sensor overview. Based on these findings it is concluded that the collected data is accurate and trustworthy.

As mentioned in Method, next to mechanical sensors, biosensors were integrated as well. A visual overview of the Heart Rate and Galvanic Skin Response is visualized in Figure 6, Biosensory data.

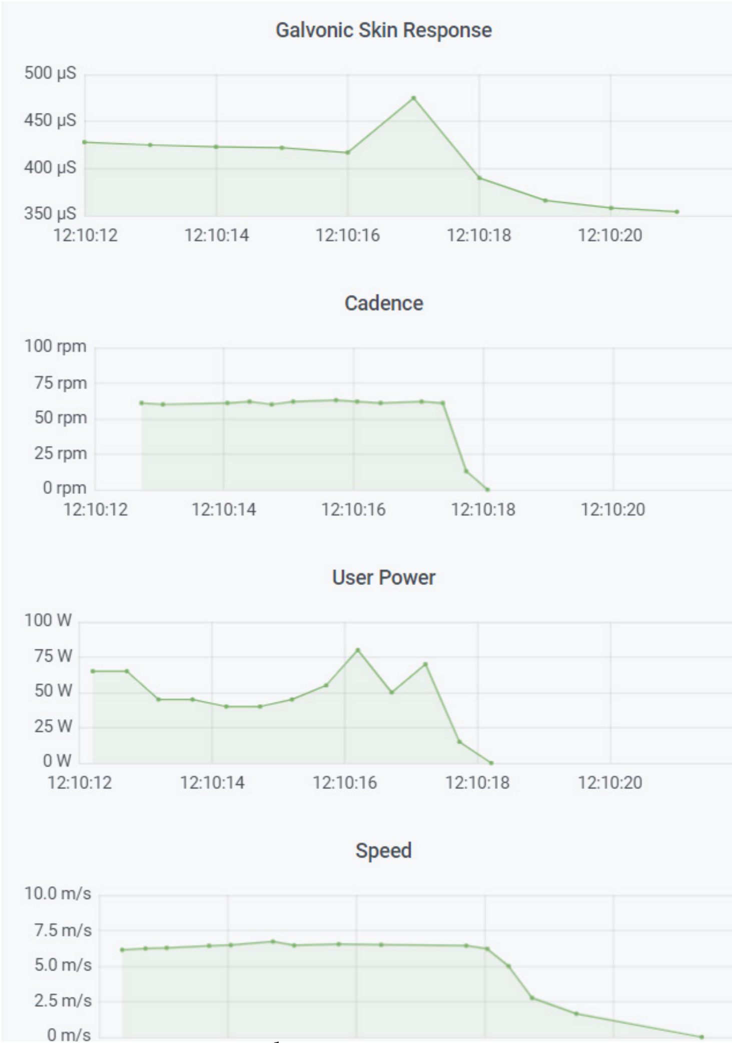

Figure 8, emergency stop data

4.3 Analysis

It proved to be feasible to subscribe to the internal mechanical sensors inside the Bosch motor system. Since these sensors were not implemented by us it is difficult to determine how accurate they are. However, looking at the results they do look correct. The speed was most easy to validate using a second GPS based speedometer and proved accurate. The frequency of collecting data was sufficient and there were only a few null values (approximately 1 per 5 minutes). It is not clear whether that was caused by our system or by the sensors themselves. However, since it did not occur at multiple sensors simultaneously, it is likely to be a sensor issue. It is not extraordinary to miss a few values when capturing and sending thousands of data points. The module that was built proved to be really stable and after running has not once failed.

The biosensors have proved to be feasible as well, as long as there is direct contact with the subject. For this study an off-the-shelf Apple Watch measured heart rate, so that was expected to work. The GSR was made using a microcontroller and proved feasible as well. The graphs and visuals of the biosignals themselves do not show us insights except it proves operation. The interesting part lies in combining multiple data charts. For example, heart rate could go up all of a sudden, but it was hard to determine whether this was caused by increasing the bike's speed, a scary emotional experience or climbing a steep slope. However, when combining the increase in heart rate with the cadence, speed, and user power the context becomes clearer. An increase in user power leads to an increase in heart rate. The rider has to deliver more energy, and this will trigger his/her heart rate to go up. It is possible to revolve that statement. If the rider's heart rate goes up, but user power remains the same it is very likely that the increase is caused by some emotional experience.

Another really interesting observation is the fact that the GSR sensor quite clearly shows spikes (see Figure 6, Biosensory Data). These spikes are triggered by the rider's environment, a clear reaction to sudden events. It has been ruled out that these are random values through the event logger, and it should also be noted that it is very likely for the heart rate to increase after a spike in GSR data. Heart rate simply lags about 10-15 seconds behind if events are triggered but it does seem to be predictable by GSR spikes.

Following up on this observation, an emergency stop was simulated. The rider was asked to take a quick tour and someone else jumped in front of the bike while riding, causing need for an emergency stop. The results of the graphs for this event are shown in Figure 8, emergency stop data. We were surprised to see that in a split second (approximately 0.5s) the GSR sensor captured a spike, before the cadence dropped, user power dropped and eventually speed dropped within 2 seconds. Apparently, in case of a stressful event it is possible to register sweat before any other indicators. The biosignal that the GSR sensor captures is quicker than the reflex of the rider to break aggressively. Basically, the data shows the biological stress reflex before the mind of the rider is able to cognitively respond with stopping to pedal and break.

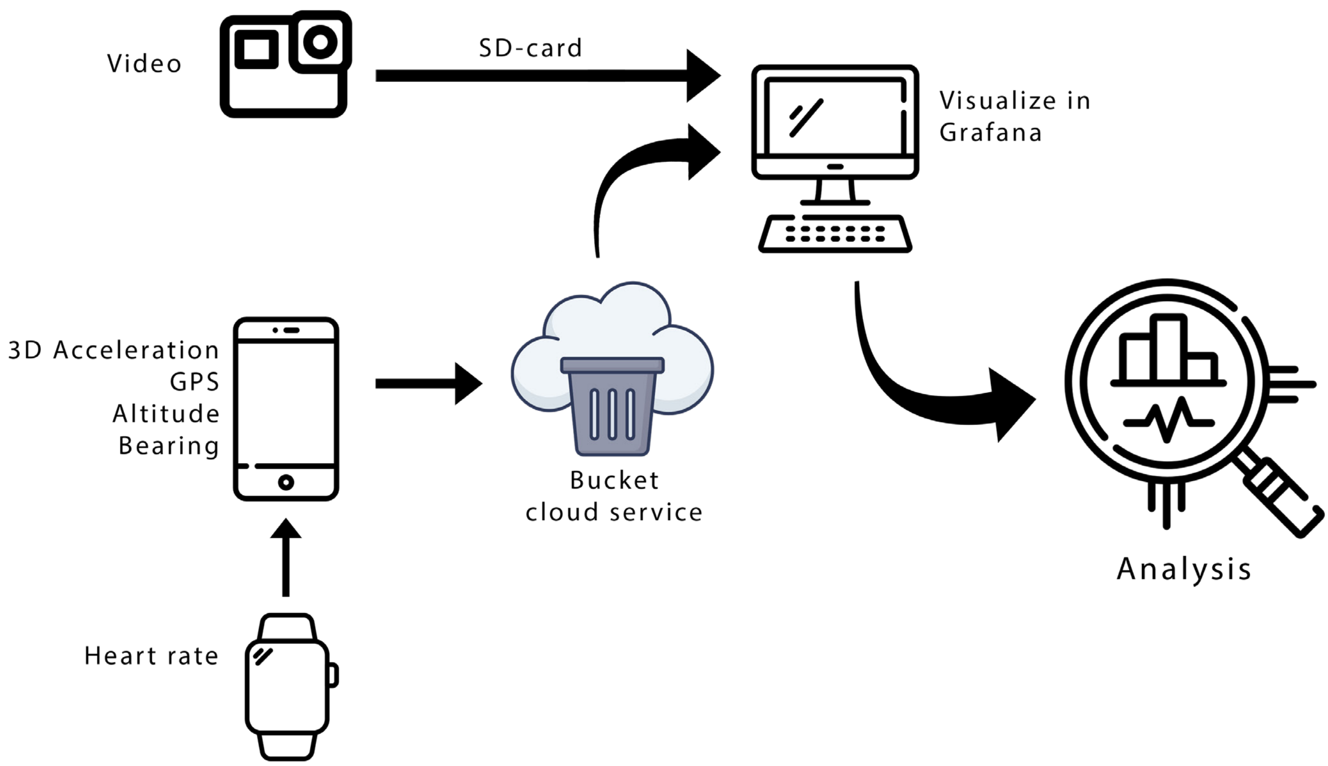

Figure 9, architecture

4.4 Implementation

The generation of data was an iterative process, with the subsequent addition of sensors to the created architecture (see Figure 9, architecture) optimizing the flow along the way. The final setup was implemented during the 3-day Smart Connected E-Bike Hackathon in Ede. For this event a demonstration was created that involved a sequence of 3 different events. Providing only the dataflows people were asked to predict the event that was triggering changes. This way people were able to (somewhat) predict the following events: A normal stop in front of a traffic light (user power & cadence dropped. Speed dropped slowly. Heart rate remained steady). An emergency stop (spike in GSR. User power, cadence and speed dropped quickly and heart rate increased). And finally, the event: escaping an ambush by kids with nerf guns, was predicted as a stressful threat (GSR spiked. Increase in user power, increase in speed and cadence and increase in heart rate). People indicated that heart rate was easier to interpret over GSR data as this was more familiar to them. This makes sense considering a heart is a highly familiar shape to people as symbol for love and life. People are familiar to the sound of their own heartbeat. Have probably seen heart rate graphs in hospital rooms (in movies or series). The fact that heart rate sensors are increasingly integrated in our lives (Apple watch/fitbits) also prove a consumer interest and understandability of heart rate data. Measurement of heart rate data can be done by placing at least 2 electrodes on the skin to measure electrical activity originating from the heart, or by making use of Optical Heart Rate Monitoring (OHRM) to measure the expansion of blood vessels (Valencell, 2022). It is possible to fully integrate these sensors into the handlebars of the E-bikes as commercially available products show. However, for this study separate sensors are being used.

4.5 Discussion

The results of this explorative prototyping phase indicate that it is easy to collect data within an E-bike context. It proved possible to subscribe to the dataflows that already exist within the E-bike controller. This enabled us to extract the user power, cadence, speed and more right out of the already existing sensors. Making use of the available sensors is cheaper, quicker and likely more accurate. Next to the existing sensors, new ones were implemented. The most important being two biosensors to measure Galvanic Skin Response and Heart Rate. The combination of the biosensors and mechanical sensors provided us with a better understanding of the possible context and state of the rider. The Galvanic Skin Response sensor was hard to interpret for people. The results of implementing the sensors and creating the live overview in context was presented to about 30 people during a Hackathon. Many of them indicated that the heart rate data was more familiar, recognisable and relatable.

The ease of implementation for different sensors on e-bikes was in line with our research. Even though ease of implementation was expected, it was unexpected to be able to get into the motor-computer communication so easily. It was assumed that commercial companies would try to shield as much information as possible but this was not the case for Bosch. It fits in line with this novel market that is under heavy digital development. E-bike manufacturers have realised that their product is suitable for data collection, but they do not know how to monetize it yet. This phenomenon is described as the Digitalization Paradox (Bosch, 2022). COBI is set up as a marketplace that enables developers to create applications for their dataflows. Giving people access to the data and see what they come up with might be a strategic business strategy. The challenge lies in including biosensors as most of them require direct contact with the rider. There are some solutions with integrated heart rate sensors in handlebars but these seem undeveloped. It makes sense that GSR is considered less ease to interpret over heart rate data. People are familiar with the sound of their heart beat since the day they were born. In almost every context the heart rate is a sign of life, sweat is not integrated into our lives as much.

It was beyond the scope of this study to generate deep insights into the implementation of specific sensors into an E-bike. This limits detailing in the way sensors register, store and send data. The overall architecture is elaborated but there is little in depth information on the technical aspects of the sensors themselves. Also, only two biosensors have been implemented, whereas these proved to be most promising. Furthermore, implementing more sensors in an explorative phase is probably always beneficial. Even though many different sensors were investigated, this could always be elaborated.

Further research is needed to establish more detailed insights regarding the implementation of a fully smart connected e-bike. There should be more investigation into other biosensors, preferably sensors that do not require direct contact with the subject but could be integrated into the e-bike. For example, it would be beneficial to take a deeper dive into integrated heart rate sensors and GSR sensors into the handlebars of bikes.

4.6 Conclusion

During the described phase many insights into the feasibility of sensors were found and implemented along the way. Implementing mechanical sensors proved feasible by making use of the existing sensors in the provided E-Bike. These sensors were captured through the Software Developer Kit provided by Bosch within the COBI. bike application. Biosensors often have the requirement of direct contact with the subject and can be implemented if that provides no issue. Biosensors proved again to be very interesting with regards to understanding the physical and emotional state of the rider and gaining insights in the context and events that are happening. Heart rate is a slow indicator often lagging 10-15 seconds behind occurrences but is easily recognised and interpreted by people. Galvanic Skin Response (sweat) sensors are less familiar to people but indicate a higher accuracy in accurately and quickly predicting (emotional) events through spikes. GSR sensors seem to be quicker than human reflexes or cognitive reactions. Requirements for a Smart Connected E-Bike seem easily surmountable as proved with implementing most sensors within a few weeks of prototyping.

> *RQ = What (bio)sensors are suitable for implementation within E-bike context in order to provide (behavioural) data?*

As suggested in Chapter Introduction, it is demonstrated that E-bikes provide an excellent context to implement sensors. It is demonstrated that the implementation of most promising sensors was feasible. The final results show the implementation of the following sensors: speed, user power, cadence, event logger, GSR and heart rate. Also, during the process it was proved possible to capture video, audio, ambient light, acceleration, gyroscope, magnetometer, direction, GPS, altimeter, and steepness. However, these sensors were deemed less relevant for understanding the context in this study. The main limitation when implementing sensors within E-bike context is considered biosensors as these often need to be wearables. Next to the sensors, predicting emotional states for riders seemed promising for multiple stakeholders. A proposal was made to automatically predict events using pattern recognition and label them accordingly. This was not investigated further as it would not help answering the research question. The TU Delft team was awarded the 'Most Innovative Solution' award at this Hackathon, concluding the prototyping phase with dignity.

Figure 9, Hackathon Winners

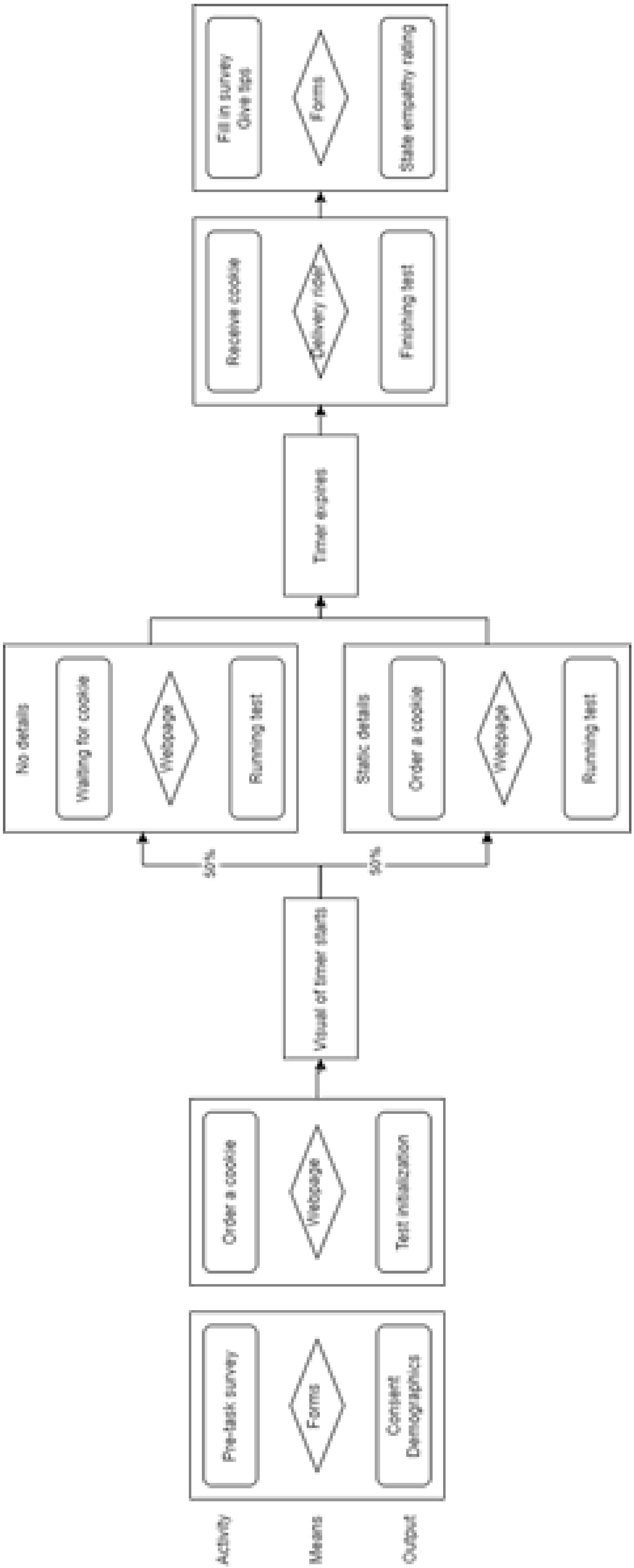

Figure 10, Test flow

5. Part II - Objectives & Method

In order to validate the second part of the previously mentioned Research Questions, an experiment was proposed to generate quantitative substantiation for accepting or rejecting the hypotheses. This research has been set up in consultation with professors employed by the TU Delft and with approval from the Human Research Ethics committee (HREC). The study has been conducted at the faculty of IDE at the TU Delft in the Netherlands from 02/06/2022 until 13/06/2022. In order to explore any causal relationships between presented data and its effect on evoking empathy, an experimental beverage delivery test has been created and performed. The methodological approach is described below.

RQ3.1 = How (significantly) does showing static personalized data to the consumer influence experienced empathy towards a delivery rider?

RQ3.2 = How (significantly) does showing live biosignal data to the consumer influence experienced empathy towards a delivery rider?

5.1.1 Beverage delivery test

This sub study is designed to quantify the difference in experienced empathy by the participant towards a delivery driver with regards to the information that is shown. The study is designed to establish a cause-and-effect relationship. It would be favourable to establish a significant relation. However, the output data will mainly be collected using a questionnaire consisting out of nine 7-point Likert scale questions. Therefor it is anticipated that the results will likely be indicative and not statistically significant enough to determine a solid cause-and-effect relationship. To capture the experience, the participant will order a beverage through our mock-up of a fictional delivery service. While waiting for the beverage to arrive there will be three different informational pages that are shown to the participant:

A) - Null: the participant will see an order confirmation and ETA of delivery. The timer will be set to 3 minutes and then run until -2 minutes. They will receive the beverage.

B) - Static: the participant will see an order confirmation, an ETA of delivery and static personalized information regarding the delivery rider. The timer will be set to 3 minutes and then run until -2 minutes. They will receive the beverage.

C) - Dynamic: the participant will see an order confirmation, an ETA of delivery, static personalized information regarding the delivery rider and live data containing biosignals from the rider. The timer will be set to 3 minutes and then run until -2 minutes. They will receive the beverage.

The level of empathy will be defined using the Measure of State Empathy (from here on; MSE) which is a method to explore the state determinants of empathy divided in cognitive, affective and compassionate types of empathy (P. Powell, 2016). The difference between these types are defined (C. Batton, 2009) & (B. Cuff, 2016) and are, for simplification, all considered equally relevant.

First, a pilot will be held with a smaller group of students (N = 10) to assess its suitability for our research questions and to establish practical hurdles. After improving the practical test flow based on the findings during the pilot the empirically designed study will be held with more participants (N = 60) in order to answer the previously formulated research questions. To see the results and changes made after the pilot refer to Appendix A, pilot findings.

The flow of the experiment will be as follows. At the start the participants will sign an informed consent form and receive a brief questionnaire to establish basic demographics. The participant will be asked to order a beverage using our mock-up for a beverage delivery service on a provided mobile phone. After doing so, they will receive a confirmation of the order and a timer of 3 minutes will start to run. To slightly decrease the standard level of empathy, the delivery will be late resulting in the timer running 2 minutes overtime. During waiting, the participant is allowed to spend their time any way they please in order to mimic a realistic context. After 5 minutes the delivery driver will arrive on foot and hand over the beverage. The participant will confirm receiving the beverage in the FastDrink application and consequently is asked to give a 5-star rating for the application in general, delivery time and delivery rider. Afterwards, some questions are asked to establish an indication of the amount of interest the participant had for the FastDrink application. Finally, the participant will be asked to fill in the MSE questionnaire and some brief semi-structured observations will be noted by the researcher to inquire what was easy/difficult during the test and to register any other possible remarks.

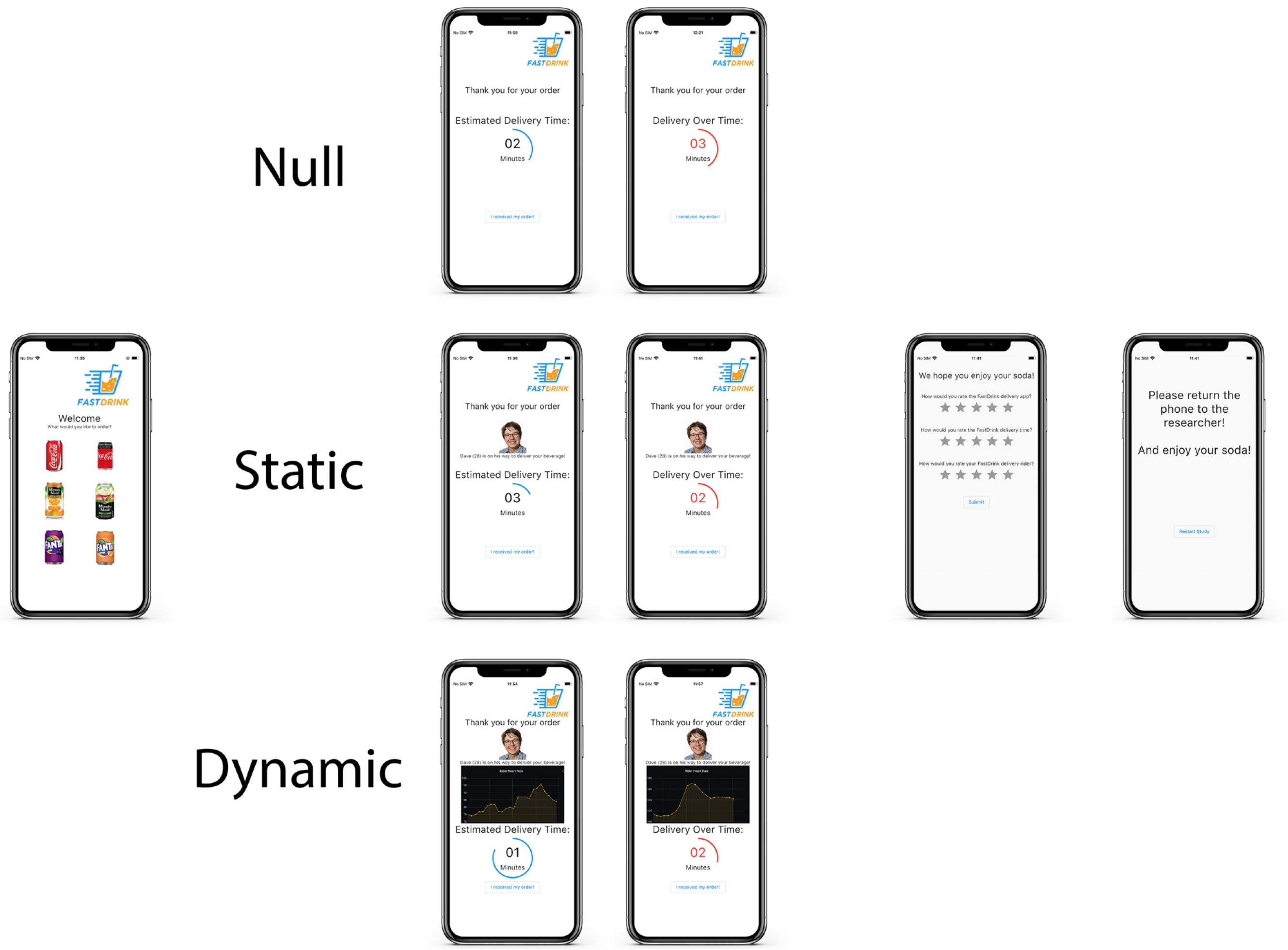

Figure 11, UX application

5.1.2 Stimuli

Every participant (N = 60) was shown one of three pages containing different communicatory data content described as stimuli. The three different pages; Null, Static and Dynamic are detailed below. The choice of delivering beverages was made because it was considered the most consistent product with regards to desirability by the 'consumer'. Food/snacks were considered to be more dependent on how hungry the participant would be, influencing how fulfilled someone would be with the delivered product. Whereas participants were considered more constant in their desire for a drink. To decrease the chance of people not liking the product they were allowed to order, six options were presented out of the most common beverages found in Dutch supermarkets: Cola, Cola Zero, Fanta Orange and Fanta Cassis. Apple juice and orange juice were included to provide participants with a (semi-)healthy option as well. Next to picking the drink, the mock-up application was made as low-profile as possible using only a basic logo and name. Students were asked to "participate in a study regarding a fast beverage delivery service on campus, allowing them to order a drink if they agreed to answering a few questions". This research has been conducted within the faculty of Industrial Design Engineering. It is acknowledged that the dataset only includes results from students (average age = 22,5 years) which limits the data diversity. To review the UX of the application refer to Figure 11, UX application.

As mentioned above, the timer of the expected delivery time will deliberately overrun. The purpose of the rider being late is to decrease a standard positive attitude towards someone since the service is free. The participants were informed that the service was a fast delivery service, therefore a total of 5 minutes delivery time was chosen.

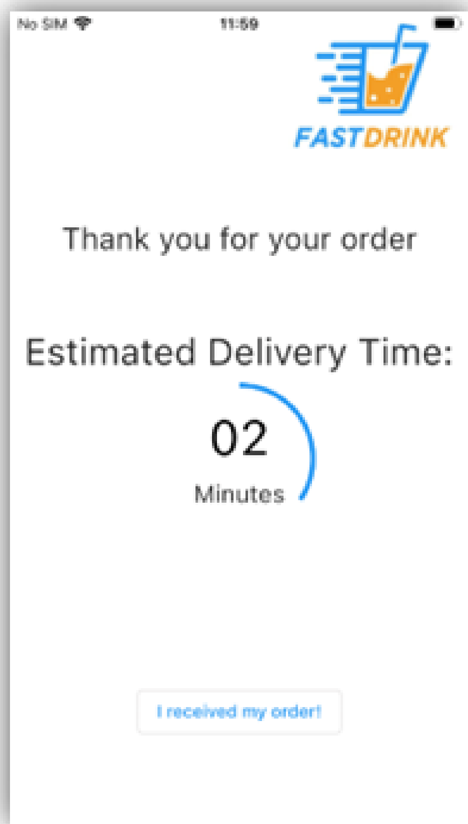

Figure 12, Figma screencap of page A (Null)

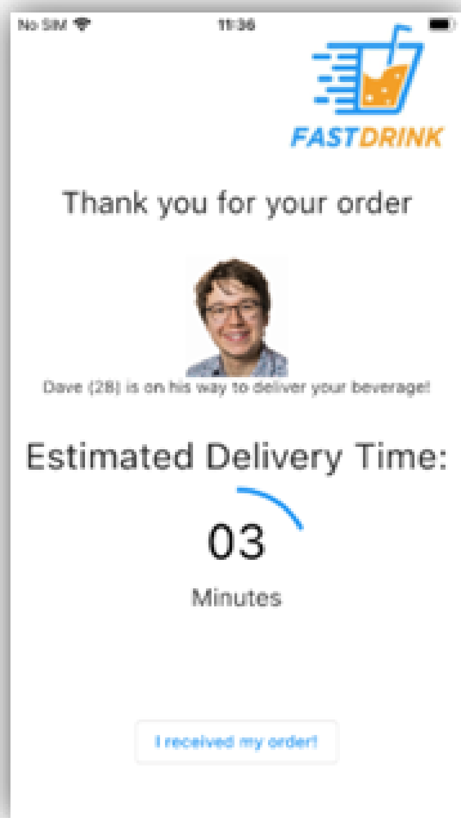

Figure 13, Figma screencap of page B (Static)

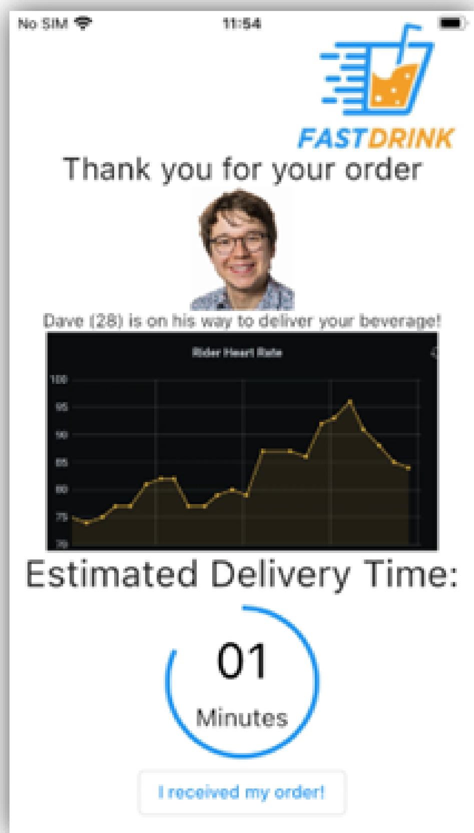

Figure 14, Figma screencap of page C (Dynamic)

5.1.3 Null Page

The purpose of the Null page is ruling out any standard influences on empathy and establishing a baseline. The Null page should allow us to define what the standard amount of measured empathy is in order to check whether there is an increase solely triggered by incrementing the information that is shown. The layout of the page was designed as can be seen in Figure 11, Figma screencap of page A (Null).

5.1.4 Static Page

For the Static Page personalised information regarding the delivery rider was created. Following guidelines found during research (see Chapter Static Data) the following information was added: age, name, and photo. The photo and age matched the actual physical of the delivery rider. For the name a general alias was chosen to be a general English first name; Dave. Screen snaps of the Static Page flow can be found in Figure 12, Figma screencap of page B (Static).

5.1.5 Dynamic Page

To create the Dynamic Page, an incremental approach was chosen to exclude possible diminishing of empathy due to removing the Static information. This enables an accurate analysis of the data when checking the change in state of empathy between the Static Page and Dynamic Page. Following guidelines synthesized during the Dynamic Data research biosignal data was added in the form of a live heart rate. Research indicated the choice for a bio signal and during prototyping it was concluded heart rate was easier to interpret over GSR data. For this research the heart rate data was not actually updated live but a pre-recorded sample set to make sure all participants were exposed to the exact same dynamic information. Screen snaps of the Dynamic Page can be found in Figure 13, Figma screencap of page C (Dynamic).

5.1.6 Questionnaires

All questionnaires can be found in Appendix B, Questionnaires.

Measure of State Empathy (MSE)

Self-report questionnaires are a fast and easy-to-administer tool for assessing empathic experience and behaviour (Reniers, Corcoran, Drake, Schryane, & Völlm, 2011). The MSE metric is introduced by (Powell & Roberts, 2017) to measure state empathy from a person towards another specific individual. This does not include for example, brand loyalty. The MSE focusses on three different types of empathy, which are distinguished but for this research treated as equally influential. Data is collected through a 7-point Likert scale (1 = not at all, 7 = entirely) which makes it easy to analyse afterwards. The questions are altered to fit our scenario by replacing 'individual' with 'cyclist'. The questions are shown in the table MSE to the left.

5.2 Results

For an overview of all the collected raw data please review Appendix C - Raw Data. During the testing phase a few unforeseen errors occurred with the participants which led to burning entries 0, 5, 39, 57 & 58.

#	Question	Cognitive / Compassionate / Affective	Alias
1	I understood how the cyclist I was interacting with was feeling	Cognitive	C1understand
2	I knew what the cyclist I was interacting with felt emotionally	Cognitive	C2emotion
3	I could identify the feelings the cyclist was having	Cognitive	C3identify
4	The cyclists' feelings transferred to me	Affective	A1transfer
5	I felt the same way as the cyclist I was interacting with	Affective	A2feeling
6	I experienced the same emotions as the cyclist	Affective	A3experience
7	I had feelings of concern for the cyclist I was interacting with	Compassionate	P1concern
8	I experienced feelings of sympathy towards the cyclist	Compassionate	P2sympathy
9	I felt a sense of compassion for the cyclist	Compassionate	P3compassion

5.3 Analysis

For the analysis of the results multiple statistical tests as well as more extensive exploring analyses were done within SPSS and R. The data has not been pre-processed in order to ensure or enhance performance. First, the Shapiro-Wilk test was done to test normality and the Levene's test to test homoscedasticity. If the results turn out they are not following a gaussian distribution a Kruskal-Wallis test for the three separate groups (Null, Static, Dynamic) will be done followed by a Wilcoxon test. However, if the data does follow the bell curve it is preferred to perform ANOVA tests on all three separate groups followed by individual t-tests between two groups. Afterwards, a more explorative approach will be done for each individual question using Principal Component Analysis, one of the most commonly used unsupervised machine learning algorithms. The objective is to test the hypotheses:

> *H3.1 = A<B - Static personalized data (B) will evoke more empathy than the Null page (A).*
>
> *H3.2 = B<C - Live biosignal data (C) will evoke more empathy than the Static personalized data (B).*

The final dataset contains 63 participants (N = 63). The means, standard deviations and other descriptives are best described in Table 1, descriptives.

5.3.1 Normality test

In order to test the distribution of the data, a test of normality was performed. For this test, the hypothesis is that the data is normally distributed approximately following the gaussian curve. In order to reject this hypothesis, meaning that the data is not normally distributed the p value has to be below the alpha level. The alpha level is set to the general 0.05. Using the Shapiro-Wilk test, the following significances were calculated: 0.98, 0.257, 0.185 (see Table 2, test of normality)

For all of the three SEQ (State Empathy Questionnaire) scores, the p value (= Sig.) > 0.05. Therefore, these scores are validated as normally distributed. Next to testing the three SEQ scores, the Z-scores for the different states of empathy were calculated. The Shapiro-Wilk test was also performed on these scores of which you can find the results in Table 3, z-score normality.

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
SEQ_cognitive	.00	23	8.48	2.968	.619	7.19	9.76	3	14
	1.00	20	8.50	3.606	.806	6.81	10.19	3	15
	2.00	20	10.15	4.380	.979	8.10	12.20	3	19
	Total	63	9.02	3.687	.465	8.09	9.94	3	19
SEQ_affective	.00	23	9.91	3.579	.746	8.37	11.46	4	17
	1.00	20	9.50	3.720	.832	7.76	11.24	3	16
	2.00	20	9.95	3.236	.724	8.44	11.46	5	18
	Total	63	9.79	3.469	.437	8.92	10.67	3	18
SEQ_compassionate	.00	23	9.22	3.261	.680	7.81	10.63	3	15
	1.00	20	9.05	3.790	.848	7.28	10.82	3	17
	2.00	20	9.80	3.548	.793	8.14	11.46	4	17
	Total	63	9.35	3.483	.439	8.47	10.23	3	17

Table 1, descriptives

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
SEQ_cognitive	.116	63	.033	.968	63	.098
SEQ_affective	.107	63	.070	.976	63	.257
SEQ_compassionate	.095	63	.200*	.973	63	.185

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Table 2, test of normality

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
z_cognitive	.088	63	.200*	.982	63	.464
z_affective	.087	63	.200*	.978	63	.328
z_compassionate	.070	63	.200*	.979	63	.348

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Table 3, z-score normality

In this case interpretation results in the same conclusion, the p value for all three states (= Sig.) > 0.05 therefore it is considered normally distributed.

It should be noted that normality tests typically have low power in small sample sizes. However, the sample size used (N = 63) is considered large enough to perform normality analysis. Also, because of the medium sample size the focus lies on Shapiro-Wilk instead of Kolmogorov-Smirnov which is typically used for larger sample sizes.

5.3.2 Homoscedasticity

Next to the normality tests, Levene's test was performed to test the difference in variances for the three states. The test compares the standard deviation to check whether the error rates between data groups are similar instead of one with a small error rate and one with a huge spread of error rates. The hypothesis states that there is no difference between the variances, so they are equal. If Sig. is greater than 0.05, non-equal variances are assumed. For ANOVA testing on datasets equal variances are not necessary if the sample sizes are equal. For this dataset, as can be seen in Table 1, descriptives, the sample sizes are almost equal.

In Table 4, homoscedasticity, Levene's test shows that the variances for the z_cognitive score were not equal, $F(2,60) = 1.977$, $p = .147$. For the z_affective were not equal, $F(2,60) = 0.413$, $p = .160$. And for z_compassionate were not equal, $F(2,60) = 0.030$, $p = .970$. Since the sample sizes are similar (20, 20 & 23) equal variances are not a necessity thus the data is considered suitable for running ANOVA tests.

The Levene's test for the Z-scores provide the same conclusion. All p values are above 0.05 and thus not homoscedastic. The scores are visualised in Table 5, homoscedasticity z-scores. Since the scores do not provide new conclusions or insights from here on analysis on the SEQ-scores have been done leaving the Z-scores out.

It should be noted that any hypothesis test is more likely to be statistically significant if performed on a large sample size. However, if N > 30 and there is not much difference between sample sizes then Levene's test is considered robust which is the case.

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
SEQ_cognitive	Based on Mean	1.912	2	60	.157
	Based on Median	1.567	2	60	.217
	Based on Median and with adjusted df	1.567	2	53.759	.218
	Based on trimmed mean	1.827	2	60	.170
SEQ_affective	Based on Mean	.581	2	60	.563
	Based on Median	.480	2	60	.621
	Based on Median and with adjusted df	.480	2	59.090	.621
	Based on trimmed mean	.558	2	60	.576
SEQ_compassionate	Based on Mean	.293	2	60	.747
	Based on Median	.314	2	60	.732
	Based on Median and with adjusted df	.314	2	57.601	.732
	Based on trimmed mean	.293	2	60	.747

Table 4, homoscedasticity

Test of Homogeneity of Variance

		Levene Statistic	df1	df2	Sig.
z_cognitive	Based on Mean	1.977	2	60	.147
	Based on Median	1.621	2	60	.206
	Based on Median and with adjusted df	1.621	2	53.488	.207
	Based on trimmed mean	1.889	2	60	.160
z_affective	Based on Mean	.413	2	60	.664
	Based on Median	.354	2	60	.703
	Based on Median and with adjusted df	.354	2	58.858	.703
	Based on trimmed mean	.402	2	60	.671
z_compassionate	Based on Mean	.030	2	60	.970
	Based on Median	.019	2	60	.981
	Based on Median and with adjusted df	.019	2	56.637	.981
	Based on trimmed mean	.025	2	60	.975

Table 5, homoscedasticity z-scores

5.3.3 ANOVA

Since the data samples for the SEQ scores are normally distributed and are homoscedastic the ANOVA test is performed for all three states of empathy (Cognitive, Affective and Compassionate).

The hypothesis states the datasets have significantly differing means and are thus proving to be accurate indications of influence by the independent variables. Since p (Sig.) > 0.05 (see Table 6, ANOVA test on SEQ-scores) there is no significant statistical difference between the means of the three different pages.

5.3.4 T-Test

To investigate whether there is an individual difference between the pages for each SEQ-score, six T-tests were done. First, the difference between the Null (A) and Static (B) (hypothesis = A < B) page was analysed for the SEQ_cognitive score. Then the difference between Static (B) and Dynamic (C) (hypothesis = B < C). This was done for the other two SEQ-scores as well. Since the hypotheses all state that one set is larger than another, the one-sided p-values are considered as opposed to two-sided p-values where the hypothesis would be A ≠ B. The results of the derived p-values are shown in the table below (p-values t-test). The results of the complete analyses can be found in Appendix D - t-test. The p-values are derived from the tables by taking the one-sided p-value column and the 'equal variances not assumed' row (see Homoscedasticity).

p-values t-test	Null vs Static	Static vs Dynamic
SEQ_Cognitive	0.492	0.101
SEQ_Affective	0.357	0.343
SEQ_Compassionate	0.439	0.261

For all p-values the statement p > 0.05 applies. Therefore, all our hypotheses are rejected and there is no statistically significant proof of any increase in empathy because of the pages using these tests.

Since the SEQ-scores are accumulations of 3 different questions, it is suggested that the questions are not accurate enough to be combined. To investigate what the statistical difference between the individual questions is, nine individual ANOVA tests were done for each question. The questions were redefined for analysis to their aliases which can be found in Table MSE questionnaire. As visible in Table 7, individual ANOVA, the significance of all questions is p > 0.05 so not a single question proved to be dependant in a statistically significant manner.

		Sum of Squares	df	Mean Square	F
SEQ_cognitive	Between Groups	37.695	2	18.847	1.404
	Within Groups	805.289	60	13.421	
	Total	842.984	62		
SEQ_affective	Between Groups	2.541	2	1.271	.103
	Within Groups	743.776	60	12.396	
	Total	746.317	62		
SEQ_compassionate	Between Groups	6.254	2	3.127	.251
	Within Groups	746.063	60	12.434	
	Total	752.317	62		

		Sig.
SEQ_cognitive	Between Groups	.253
	Within Groups	
	Total	
SEQ_affective	Between Groups	.903
	Within Groups	
	Total	
SEQ_compassionate	Between Groups	.778
	Within Groups	
	Total	

Table 6, ANOVA test on Z-scores

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
C1understand	Between Groups	3.654	2	1.827	.851	.432
	Within Groups	128.759	60	2.146		
	Total	132.413	62			
C2emotion	Between Groups	4.236	2	2.118	1.022	.366
	Within Groups	124.367	60	2.073		
	Total	128.603	62			
C3identify	Between Groups	.503	2	.252	.111	.896
	Within Groups	136.576	60	2.276		
	Total	137.079	62			
A1transfer	Between Groups	5.447	2	2.723	1.001	.373
	Within Groups	163.157	60	2.719		
	Total	168.603	62			
A2feeling	Between Groups	7.606	2	3.803	1.965	.149
	Within Groups	116.109	60	1.935		
	Total	123.714	62			
A3experience	Between Groups	2.481	2	1.241	.670	.516
	Within Groups	111.170	60	1.853		
	Total	113.651	62			
P1concern	Between Groups	9.894	2	4.947	1.516	.228
	Within Groups	195.852	60	3.264		
	Total	205.746	62			
P2sympathy	Between Groups	3.176	2	1.588	.573	.567
	Within Groups	166.252	60	2.771		
	Total	169.429	62			
P3compassion	Between Groups	15.106	2	7.553	2.907	.062
	Within Groups	155.878	60	2.598		
	Total	170.984	62			

Table 7, individual ANOVA

Based on these findings it was concluded that it would be improbable to find any statistically significant differences using the current analysis approach. Instead of validating hypotheses with significant differences for quantitative insights, a more explorative approach was tried. The previously stated conclusion that the SEQ-scores are wrongfully combined, and the questions should be analyzed separately was taken into account. This proved to be a right conclusion in the next analysis.

5.3.5 Principal Component Analysis

In order to gain more explorative insights, instead of quantitative validation which proved difficult, a simplification of the data was made using Principal Component Analysis. By making use of this form of analyses, significant conclusions can be drawn from the data at hand. Through the automated simplification of the data, some entries will be lost but the results still cover most (66%) of the data. This is the same technique that is applied within factor analysis. The analysis is considered to be just if the new dimensions combined contain over 60% of the datapoints (Hair, Black, Babin, & Anderson, 2014). Next to the reduction in data, the PCA also provides with a more visual overview of the intervariable correlations. As concluded during the previous chapter, the MSE questions will be treated separately instead of adding them in SEQ-scores. This should also generate insights into the relations between the questions themselves by looking at how the different variables differ from each other exploring their commonalities and differences. For elaboration on the statistical significance of the dimensions please refer to Appendix F - Accountability dimensions.

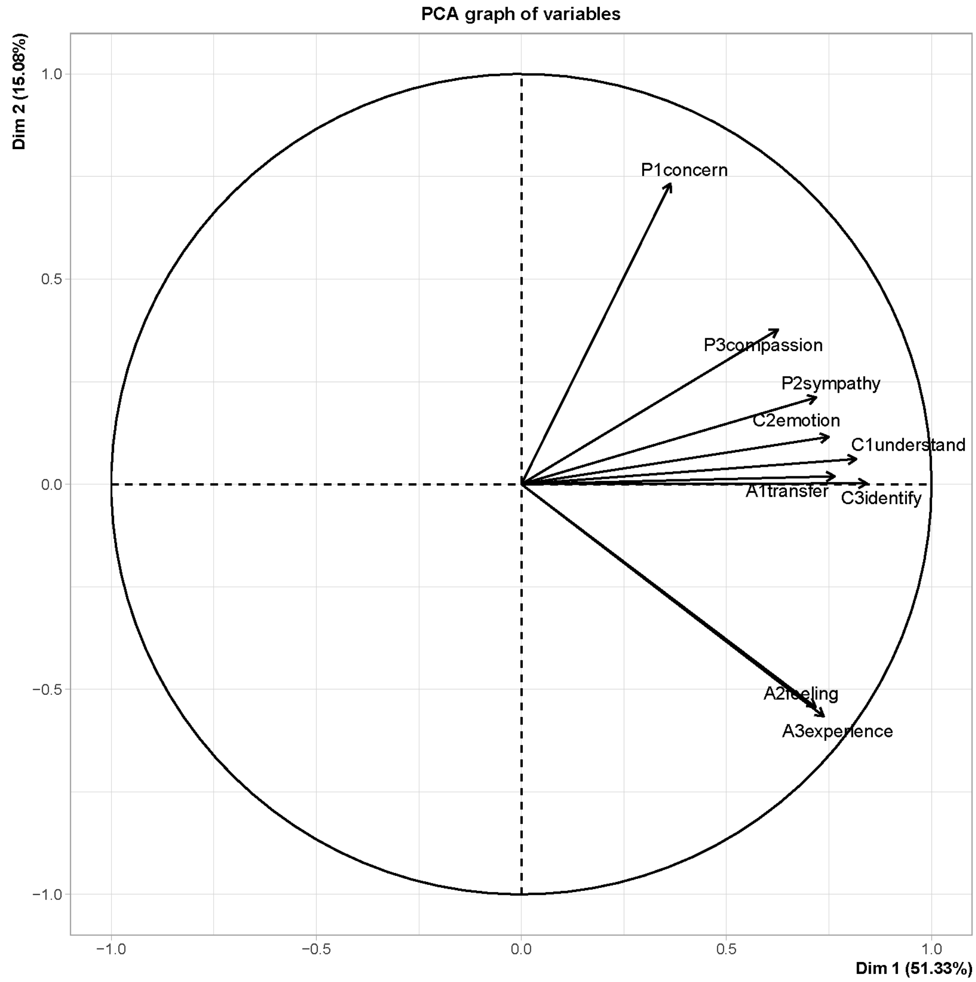

Figure 15, PCA graph of variables

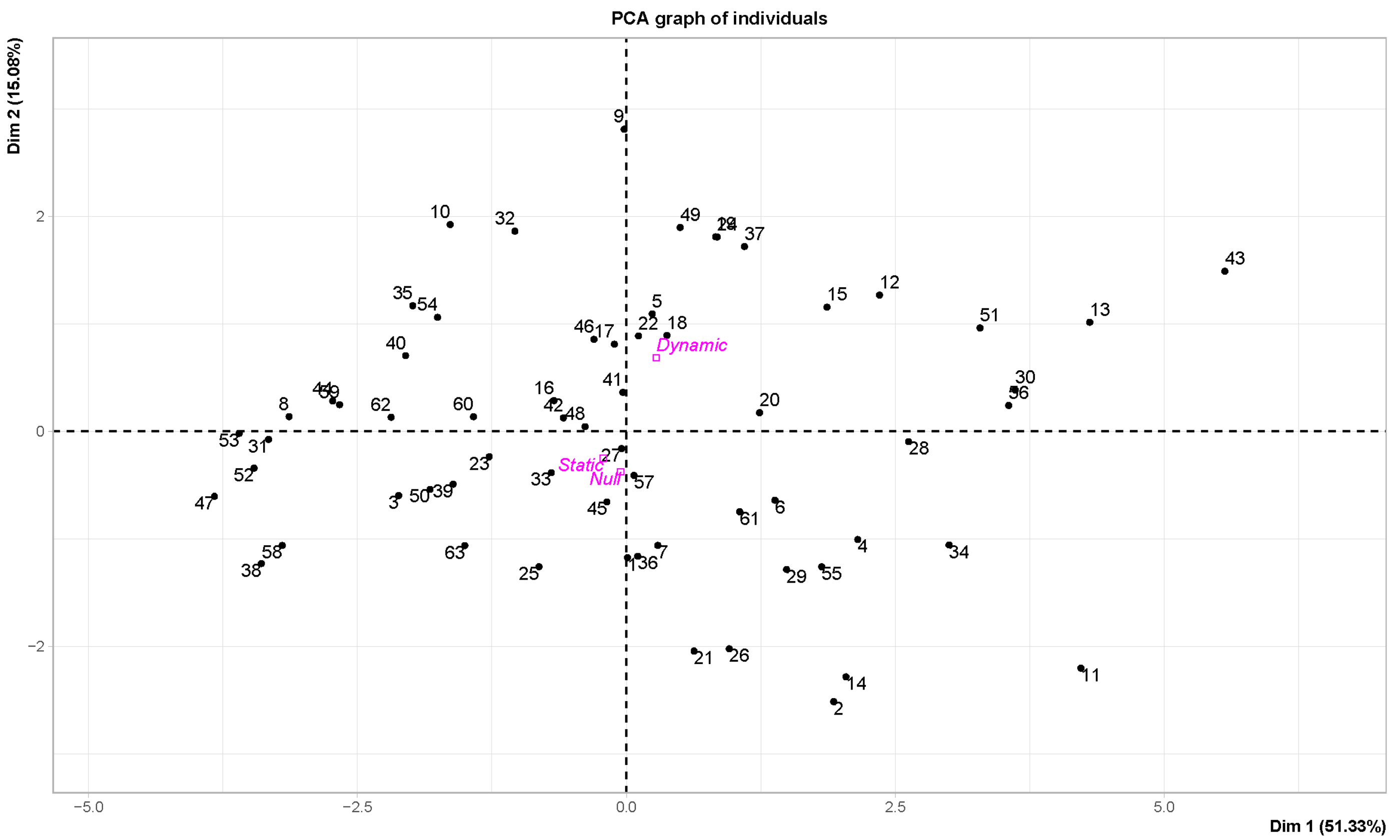

Figure 16, PCA graph of individuals

A visual representation of the PCA analysis for the separate questions is displayed in Figure 14, PCA graph of variables. The x and y axis are formed through a machine learning algorithm to simplify and reduce datapoints yet keeping as much possible. The x axis is dimension 1 (Dim 1) and covers 51.33% of the data, the y axis (Dim 2) accounts for 15.08% of the data. Meaning the x axis is considered more certain and thus more influential than the y axis. To make an educated guess, the x axis is likely to represent a certain presence of empathy, since all vectors are on the same side. The y axis seems to represent the presence of concern (compassion) versus feeling (affective empathy). Each arrow represents a single question which are derived from the MSE and can be found in Table MSE questions. The length of the vector indicates its significance. Since all vectors are close to 1 (approximately 80%) they are all considered significant.

If the arrows are overlapping (in the same direction), they show great similarities. Meaning they can be combined. For example, question A2 and A3 are strongly correlated since they show great visual similarity. Question C3, A1, C1 and possibly P2 can also be added up since they somewhat share the same direction. They show similarities at least. Question P1 is very different and negatively correlated to A2 and A3. So, it is likely that if a participant has high score on question P1, they will have a lower score on question A2 and A3. This mainly illustrates the intervariable correlations and that all the questions have a positive correlation on the x axis. It also underlines the assumption stated before that the questions should be treated individually instead of combining them into SEQ-scores.

When plotting the graph of individuals (see Figure 15, PCA graph of individuals), the correlation with the pages becomes visible. The dimensions are the same as these were determined to cover most of the datapoints by the analysis. In this graph the difference between the Null and Static pages are close to zero. Showing that they share great overlap and are not significantly influencing the answers of the MSE. However, the Dynamic page shows great differentiation indicating a certain influence on the state of empathy. The differentiation is most clear on the y-axis, thus it can be concluded that the Dynamic page evokes compassionate empathy. Affective empathy seems to have a negative influence on compassionate empathy, but still contributes positively to 'overall' empathy since it shares the positive impact on the x-axis.

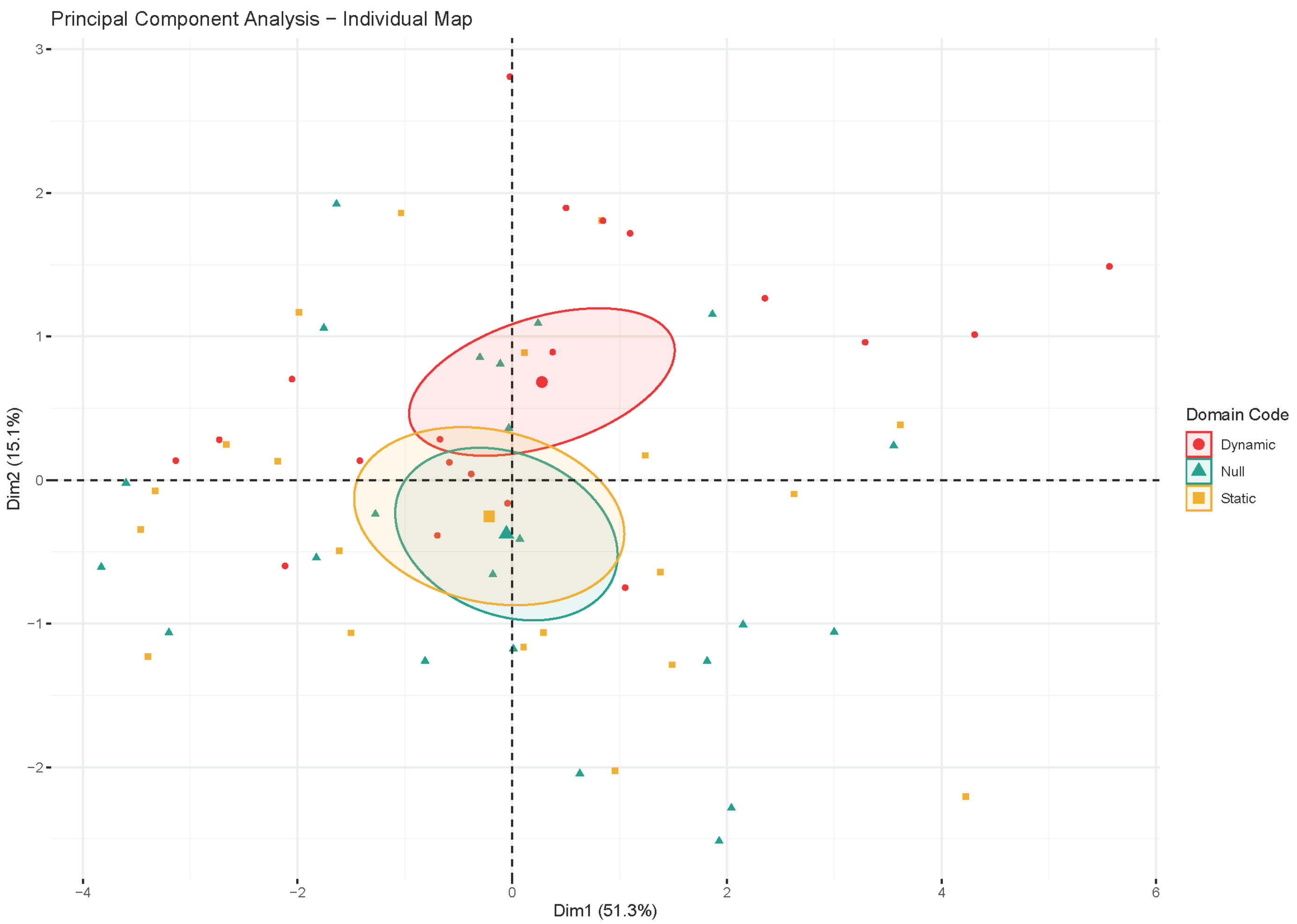

Figure 17, PCA individual map

From both graphs we can conclude that question P1 and P3 are most positively correlated with the Dynamic page. If empathy is defined as compassionate, the conclusion would be that dynamic data evokes empathy. So, when creating an app with dynamic information, it will more likely evoke compassion, cognitive – and affective empathy. Even though affective empathy seems to be opposing compassionate empathy, it is still both triggered by dynamic data.

To visualise the distribution of variances, the pages' domains are plotted within the PCA individual map (Figure 16). This more clearly visualises the similarity between the Null (blue) and Static (yellow) pages as their variances are also similar. It also underlines great differentiation between the Null & Static page and the Dynamic page revalidating that this page had an influence on the experienced empathy. Especially the influence on the y-axis differs. Indicating that the Dynamic page evokes more Compassionate empathy opposed to Affective empathy.

5.4 Discussion

The results indicate that the data is normally distributed. Also, the data is not homoscedastic but has equal sample sizes and is thus suitable for ANOVA and t-testing. However, performing these tests, no significant correlations were found between the different dependencies. It was concluded that the questions from the SEQ cannot be added together for analysis and each question should be treated individually. Further analysis using PCA resulted in more explorative insights that are considered significant. The following statements were concluded. Some questions from the SEQ show great correlation such as A2 and A3 but this does not occur for all questions. The different categories of empathy (affective, compassionate, and cognitive) show different results, indicating that the questions within categories could be analysed together. However, looking at the individual questions within these categories there are also differences. So, even though the questions of the SEQ are correlated within their domain, they can't be added together for analysis. Furthermore, looking at the effect of dynamic data, affective empathy decreases when the perceived cognitive/compassionate empathy increases. With the definition of the different aspects of empathy in mind (see chapter background) this indicated that the data increases understanding for the rider but decreases the shared feeling of the same emotions. The Static and Null page had little to no correlation to the pages that were shown. Thus, Static information has no effect on perceived empathy according to the results.

Opposed to the stated hypothesis for RQ3.1 the Static page did not evoke more empathy towards the delivery rider compared to the Null page. The data suggests that there is little to no difference between showing the Null page and the Static page. This might be due different reasons; people might be less interested in static data whereas dynamic data is more engaging. The amount of personalised data was not sufficient to make a difference. Or personified information does simply not evoke more empathy even though an increased feeling of connectedness was expected. However, in line with the hypothesis for RQ3.2 the dynamic page did increase the experienced empathy towards the delivery rider. It was also indicated that affective empathy decreases when the perceived cognitive/compassionate empathy increases. This was not expected as there was no literature found that described this effect. However, during interpretation of the results this could be explained through how the mind generally works. It makes sense that more knowledge or information generates more understanding but decreases the chances of feeling the same since there is more information to distinct yourself from as well. If your knowledge becomes more specific, it becomes less likely that you will feel exactly the same.

The experiment provides a new insight into the relationship between the different categories of empathy. Even though all empathy categories were influenced in a positive manner by the live heart rate data, there is indication that compassion and cognitive empathy are negatively correlated to affective empathy. This is a novel insight which has not been substantiated by literature before and needs further investigation (see Chapter 8, Future Work). For this research, this implicates that we have to accept a decrease in affection to gain compassion / cognitive empathy. For the stated research question (see Chapter 1, Introduction) we want to evoke empathy which is related to showing live heart rate data. The indication that dynamic data evokes empathy more than static data was predicted, however there was no indication for a difference between the Null and Static page which was surprising. This contradicts statements from state-of-the art platform services which are implementing personalized information into their applications (see Chapter 2.3, Background & Related Work/Static vs Dynamic data).

Of course, this study has its limitations. The generalizability of the results is limited by involving only participants in the same age group, with the same occupation (studying industrial design) and the same educational level. To apply the results in a broader context, it should be investigated whether this has made an impact on the results. Also, all of the participants have received a beverage for free which might tempt them to give more positive results. There was a limited choice in beverages (6 in total). All of the participants were approached to join instead of internally motivated to order a beverage because of thirst. The delivery rider was not a typical persona of a gig worker as described in Chapter 1.5, Introduction/Gig Work. However, all of these factors were influencing the three tested variables so it is assumed that the differences between them should still give an accurate representation for the influence of heart rate data on the amount of experienced empathy.

Further research is needed to establish whether there is an actual negative correlation between compassionate / cognitive empathy, and affective empathy. There seems to be a reasonable assumption for the dependency, but this should be substantiated with research. Also, the cause for the different results should be further substantiated. The test should be run with different biosignals to check the difference between using heart rate or another biosignal such as GSR. The test should be run with different ways of communication to check which way of digital communication is most influential. This study was run with a graphical visualisation, but research shows that audio might enhance empathy more (see chapter 2.3, Background & Related Work/Biosignals). The test should also be run with live heart rate data and a non-biosignal feed such as a location tracker to check the difference between live data and biosignals. Furthermore, it is advised to attract a more general participant sample and perform handover by an actual gig-worker with general working clothes.

5.5 Conclusion

From the statistical analyses on the combined SEQ-scores the conclusion should be drawn that for all p-values the statement $p < 0.05$ applies. All the generated test results have a p value of > 0.05. Therefore, all the hypotheses are rejected and there is no statistically significant proof of an increase in empathy caused by the different pages. Looking back at our research questions,

> *RQ2.1 = How (significantly) does showing static personalized data to the consumer influence experienced empathy towards a delivery rider?*
>
> *RQ2.2 = How (significantly) does showing live biosignal data to the consumer influence experienced empathy towards a delivery rider?*

Both research questions are not possible to answer with clear statistical significance. However, it has been proved that the data is definitely indicating an increase in empathy for the Dynamic page, and the Static page has little to no (significant) effect compared to the Null page. Furthermore, it is concluded that compassionate empathy is correlated the strongest with the dynamic page. Meaning that the dynamic page has had a positive effect on the compassion users experienced for the delivery rider. The data also indicates that if people have an increase in compassion, they are likely to have a decrease in affective empathy. Which could be translated to; when showing the live heart rate of the delivery rider to users, they tend to have more feelings of concern for the rider but less affection. It seems that the heart rate data induced feelings of pity instead of sharing feelings of the rider. All questions were (somewhat) positively influenced by the Dynamic page.

6. Synthesis

So far, this thesis has investigated the most important context (Chapter 2, Background & Related Work), explored different sensory options (Chapter 4, Part I) and tested the influence of heart rate data (Chapter 5, Part II). The conclusions that were drawn are described in each chapter. In order to continue with the synthesis, the first step is to have a clear understanding of the output so far.

The most important insights and conclusions have been translated into Design Drivers. These drivers will be the foundation for designing a concept that is a well-fitting solution to the stated problem (see Chapter 1, Introduction) during research. The use of Design Drivers fits a more open approach to a solution space. Instead of creating a clear list of requirements, Design Drivers focus more on a vision on where the solution should be. It is a more creative and explorative tool to create a proof of concept. For this project, there is not enough time to perform an in-depth design cycle which leads to a well-designed, thought-through final concept. In order to create a tangible output and showcase what a possible solution space could be for the formulated Research Question the focus lies on creating a Proof of Principle. The Design Drivers will be the main reasoning why the concept meets the needs and solves the problem in our context.

6.1 Design Drivers

- Evokes empathy from consumers towards delivery riders

The overarching goal of the project is to find a solution that contributes to the stated research question (Chapter 1, Introduction). The objective is to increase the amount of empathy experienced by consumers towards delivery riders. The concept should specifically evoke empathy from the receiving consumer, so the communication should be from rider to consumer. The focus lies not on generally evoking empathy but more on evoking it from the receiving customer.

- Communicate Dynamic Data

During the exploration within Chapter 4, Part I, it was concluded that the E-bike provides an excellent platform to implement sensors and collect continuous data. With a constant energy supply there is no need to limit data output and a lot of sensors are already available. This does not only provide a suitable architecture for live data, but also indicates that a lot of different sorts of data will be available in the future giving the users insight into their performance and well-being. In order to state anything about the current state or well-being of the user, multiple dataflows have to be combined in order to create understanding of the context. Communicating live data is the most promising when trying to understand the context and state of the rider. Next to being more promising, dynamic data has proved to be more engaging (Chapter 2.3.2, Background & Related Work/ Static vs Dynamic data & Chapter 5.5, Part II, Conclusion). Also, looking at the results from the beverage test (Chapter 5.4, Part II/Discussion), there is a strong indication that static data does not show any difference compared to zero data. This is substantiated by Chapter 2.3.2, Background & Related Work/ Static vs Dynamic data/Dynamic. Therefore, the concept should revolve around communicating dynamic data

- Includes biosignal (Heart Rate) data

In Chapter 4, Prototyping, it was already established that the Heart Rate data was most easy to interpret for people. It is considered more relatable than, for example Galvanic Skin Response data to which it was compared. People are familiar with the sound of a heartbeat, very familiar with the heart-shape and familiar with the distinct red color. In chapter 2, Background & Related Work, it was established that Heart Rate data was most promising for evoking empathy in person-to-person communication. It seems that humanizing the delivery rider seems to work best using human biosignal data such as Heart Rate. The effect of communicating live Heart Rate data on the experienced empathy towards delivery riders was substantiated by Chapter 5, Part II. Which showed a clear indication that the Heart Rate data had a positive impact on the experienced (compassionate) empathy in context.

- Tangible product separated from general platform application

There are a lot of ways to visualize and communicate data, digital data visualization is a thoroughly studied subject which is not the goal of this thesis. An obvious integration would be to add a live overview of data to the consumer through the pre-existing application that is used by the consumer. Personally, I felt that adding another feature to a delivery application would not be a novel addition. Therefore, I wanted to explore ways to communicate data using a tangible product.

- Improving gig-workers' repute

In Chapter 1, Introduction, the current working conditions and reputation of Gig-workers were investigated. It was concluded that not only the employers are ruthless, but the workers are experiencing bad treatment from customers as well. There is an increasing gap between gig-workers and society, due to the repute of employees. The Gig-economy is still a very novel phenomenon and needs development. The concept should therefor aim to improve the gig-workers' conditions, through improving their repute, contributing to the development of a better Gig-economy.

6.2 Conceptualization

The fundamental input for the design process, in this case formulated as Design Drivers (see Chapter 6.1, Synthesis/Design Drivers) based upon the findings during research, experimenting and testing, have been formulated. A very brief design cycle was initiated with the desire to create a proof of principle for our problem statement. The proof of principle is meant as a demonstration of what a possible practical implementation of the solution space could embody. Meaning that the concept might not be complete or perfect, but rather shows a possible implementation of a fitting solution that proves the feasibility, creates a more tangible and understandable output besides insights and could accelerate future concept development. Each driver was taken as starting point for ideation in the form of how-to's. This generated multiple solution possibilities that address different aspects of the found insights. Furthermore, the quick ideation method of 'worst possible idea' was done in a group session to generate more out-of-the-box ideas (Appendix G, Ideation).

This developed multiple offbeat and futuristic ideas. To create an accurate Proof of Principle an idea was chosen that was feasible and demonstrative for the project at hand.

The final concept consists out of a led grid that is integrated into the fabric of the regular working clothes displaying the live heart rate of the delivery rider.

The goal was to create tangible output that demonstrates a possible design solution. Therefore, focus lied on creating a working prototype rather than defining and developing the concept further. The results for Wizard of Oz prototyping the final concept are shown on the right. The prototype consists of an 8x8 Neopixel LED grid controlled by a Seeeduino microcontroller (see Figure 18, Neopixel grid) which flashes on and off at the same BPM as the measured heart rate (see Figure 18 & 19, Prototype states). Heart rate is measured using OHRM Grove Heart Rate sensor that has to be applied to a finger or wrist. Code can be found in Appendix H - Prototype code.

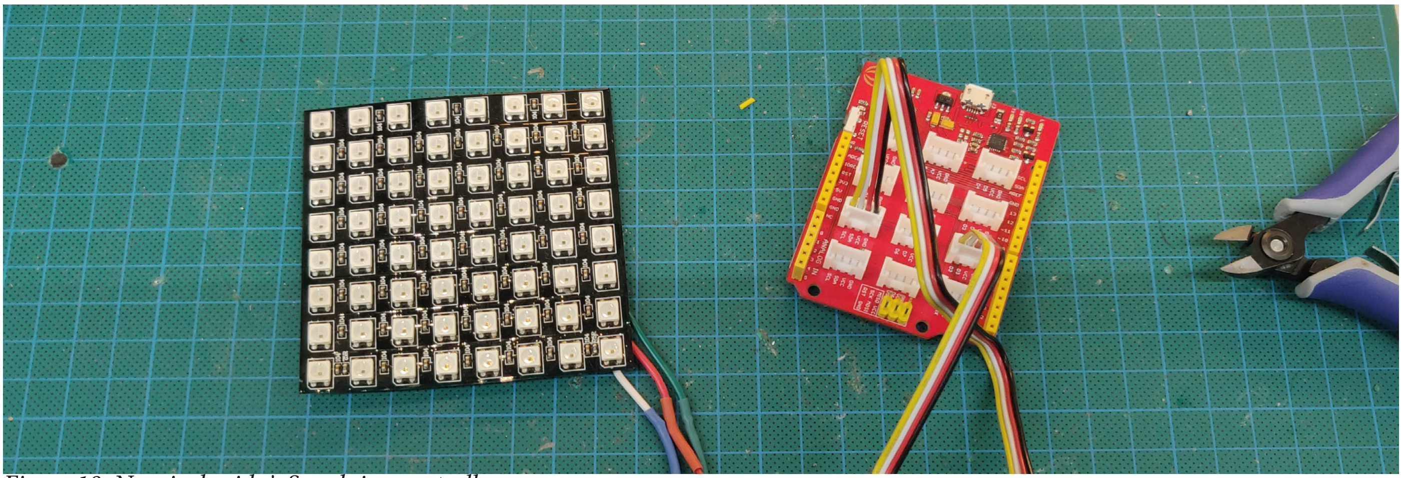

Figure 18, Neopixel grid & Seeeduino controller

Figure 19, Prototype state OFF

Figure 20, Prototype state ONN

7. Final Discussion

This thesis demonstrates that there is a need for improving the working conditions of delivery riders in the gig-economy. There is an apparent lack of empathy between delivery riders and the end-consumer. Through a data-centric design approach, the main goal is to answer;

How can empathy towards delivery riders be increased through communicating behavioral data to the consumer?

The results of the study indicate that showing the live heart rate data of the delivery rider, increases the amount of empathy experienced by the end-consumer. Through designing a proof of principle, that communicates the live heat rate data for the delivery rider towards the end-consumer, this is attempted.

During the first context research in order to further define the problem and scope the project, some insights were unexpected. It was assumed that gig-work would be a flexible job that allowed people to do perform duties on demand for a reasonable pay. However, diving into literature proved that the gig-economy is far from ideal. Instead of being the flexible innovative platform provider, most employers are involved in heavily growth oriented, loss turning enterprises that neglect their employees. Workers are treated as incidental and commutable short-term assets that are exploited. The employers attract employees that do not have many other career options and need to resort to performing uncomplicated tasks without the need of education or induction. This might be unintentional, and inherent to gig-work, but it is taken advantage of by forcing unreasonable severe non-competition and confidentiality clauses into their contracts. This is opposing the beneficial aspect of a flexible gig-economy. It was difficult to substantiate the poor relation between delivery riders and end-consumers. However, a few preliminary articles indicate that this contains a serious discrepancy between societal groups. Even though they might be exceptions, the interaction between end-consumer and gig-worker has often been experienced as unsympathetic. Diving into the definitions of sympathy, empathy and compassion led to a broader understanding of multiple related concepts that have been mapped out. For the specified context, compassion and cognitive empathy seemed most relevant as these showed understanding for someone else's effort or wellbeing. It was not considered necessary for the end-consumer to actually experience the same emotions or feelings as the delivery rider if there is more understanding.

To create more understanding of the effort, state and wellbeing of the delivery rider, sensors were added to an E-bike. It was surprisingly straightforward to implement different sensors and exploit existing sensors on e-bikes, which was in line with literature. E-bikes prove to be excellent platforms for data collection and exploration. From the results of the data exploration, it was surprising to see the clear spikes in GSR sensor data. When simulating an emergency stop, the GSR data showed a spike of less than half of a second before user power dropped. Showing the time between the biological human reflex and the cognitive decision to make a sudden stop. The GSR spikes also seemed to be very accurate predictors for an upcoming rise in heart rate. However, this was not tested thoroughly and would need further research to investigate these findings. The research continued with focus on communicating the heart rate because it was considered more relatable and easier to interpret for average consumers. Also, it was substantiated by literature that communicating heart rate evokes empathy.

During the validation on the effect of static and dynamic data on the experienced empathy, it was unexpected that the static page indicated no difference compared to the null page. This was contradicting quotes that indicated personalized static data was implemented in practice to evoke more empathy. According to our results, this proved to be ineffective. Unfortunately, there was no statistically significant difference between the live heart rate data and empathy. However, in line with the hypothesis, PCA showed a strong indication that communicating live heart rate data increased empathy towards the delivery rider. This was considered highly relevant and was a primary insight driving the design method of a final proof of principle.

The findings in this thesis provide a new insight into the working conditions of gig-workers. It establishes relevant knowledge gaps into relatively unfamiliar issues in the gig-economy. There is not a lot of substantiated literature yet regarding the relationship between gig workers and their employers. Personal findings, such as the confidentiality clause within the contract, indicate platform-based service providers deliberately try to keep information as undisclosed as possible. Multiple perspectives have been considered and demonstrate an unsustainable field of work that needs addressing. Furthermore, the study investigates the possibilities of behavioural data collection within an e-bike environment. The ease of implementation seems promising and provides opportunities for a magnitude of appliances. Using a data-centric design approach new business models or concepts could emerge from implementing (bio-)sensors.

Research into the effect of communicating heart rate data in delivery context has not been done before and could be expanded. The proposed proof of principle exhibits a way to improve the experienced empathy towards delivery riders. The results with regards to heart rate data evoking empathy are indicative for a causal effect which should be investigated further.

The reliability of this thesis is limited by an absence of final validation on the concept. The first suggestion would be to evaluate the concept as it was developed. It has to be validated whether, and to what extent, the concept evokes empathy in practice. Further limitations lie in an absence of relevant literature regarding the interaction between delivery riders and end-consumers. Also, information regarding the day-to-day experiences of gig-workers is hard to reach due to confidentiality clauses. More specific limitations have been described in Chapter 4.5, Part I/Discussion and chapter 5.4 Part II/Discussion. Finally, it should be stated that the development for the proof of concept was brief and should be iterated.

8. Future work/recommendations

Further research is needed to enhance the sensor exploration. In order to understand the state of the e-bike user, more biosensors should be implemented. The potential of combining mechanical sensors with biosensors for emotion recognition should be investigated. Future studies should take into account that GSR data might have high potential to instantly indicate stress, an increase in heart rate or other emotional responses.

Further research is needed to establish the exact cause-effect relationship of data and empathy. For example, by investigating whether: the empathy was increased by the heart rate or by biosignals in general, empathy increases by communicating live data, increasing any form of communication has an effect on empathy, the means of visualizing the data makes a difference and whether the means of communicating data has impact (audio/visual). Furthermore, the participants in the study were concurrent and should be diversified. Other specific testing recommendations are described in Chapter 5.4, Part II/Discussion. Also, the indication that compassionate and cognitive empathy are negatively correlated to affective empathy is not scientifically accounted for and needs more investigation.

Finally, further research is needed to validate the proposed concept. This proof of principle could be a starting point for a more extensive design project in which the consumer-delivery rider interaction is further studied. Reiteration through multiple design cycles, developing the proposal into a final implementation, creates a concept that increases empathy towards delivery riders.

9. Final conclusion

This research aimed to identify the problems for delivery riders and enhance their job conditions by exploring a data-centric design approach. The problem that was exposed is stated in chapter 1, Introduction where the gap between gig-workers and society due to a lack of empathy is substantiated. The novel platform-based services in the gig-economy are exploiting their employees and shift all the risk towards indefensible, disposable individuals without a well organised union. In order to improve the working conditions of delivery riders by enhancing the experienced empathy towards them, first the definition of empathy is elucidated. After defining the different categories and meanings of empathy, the final definition of "understanding another's emotions through perspective-taking" is adopted for this study.

In order to enhance 'understanding of emotions', the emotional state of the delivery rider should somehow be captured. It is proposed to do this through collecting behavioral data. Delivery riders are adopting e-bikes as their main means of transport, which proved to be excellent bases for the implementation of sensors. Through an extensive sensor exploration, data regarding the state, environment and experience of the rider bike were captured.

After capturing the data and creating a live overview to gain insights in the context of the rider state, substantiated with background research, biosignal data was determined to be the most promising output. It was decided to focus on heart rate data of the rider to evoke empathy as this was most relatable to people. Therefore, the second part of the study focused on substantiating the influence of live heart rate data on the experienced empathy within the specified context. An extensive empirical user study indicated that there was little effect of static data regarding experienced empathy from consumers. However, showing live heart rate data proved to have a positive correlation to experienced empathy towards the delivery rider.

The insights from background research, exploring sensors and extensive testing in context have been synthesized into a final proof of principle. This was done by formulating Design Drivers as main input for a brief design cycle. The final concept is presented as a showcase that aims to manifest a solution to answer the main research question:

How can empathy towards delivery riders be increased through communicating behavioral data to the consumer?

The prototype is the final manifestation that in a substantiated way proofs how empathy towards delivery riders can be increased through communicating heart rate data attempting to improve the working conditions for gig-workers that exert themselves to deliver your orders.

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Appendices