Chair of Transportation Systems Engineering
TUM School of Engineering and Design
Technical University of Munich

Cyclist Stress and Dynamic Patterns.

Identifying Instances of Cyclist Stress with Dynamic Sensors and Wearables.

A thesis presented in part fulfilment of the requirements of the Degree of Master of Science in Transportation Systems at the Department of Civil, Geo and Environmental Engineering, Technical University of Munich.

Supervisors **Dr. Ana Chou Moreno Tsui**
Associated Professorship for Travel Behavior,
Peter Matt
Bosch eBike Systems Engineering.

Submitted by **Zouheir Alameddine**
Ainmillerstrasse 29
80801 München

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Declaration

I hereby confirm that the presented thesis work has been done independently and using only the sources and resources as are listed. This thesis has not previously been submitted elsewhere for purposes of assessment.

Reutlingen, April 4th 2023

Place, Date, Signature

Abstract:

Cycling has been growing in popularity and gaining more attention as a means of reducing emissions and energy use from individual private transport. However, one obstacle that is more often mentioned by would-be users is the problem of safety. If cycling is to form a key part of a new transport strategy, these concerns must be addressed and cycling needs to become attractive to the concerned segment of the population. To understand these feelings of danger and to remedy them, they must also be understood in terms of traffic conflicts and road conditions. This thesis aims to utilize already existing methods of mapping cyclist stress and assess whether the same information can be found in the dynamic riding patterns of the cyclist. The research makes use of an experiment to naturalistically measure cyclists’ response to random traffic and road conditions while riding instrumented bicycles and equipped with wearable sensors in the Reutlingen-Tübingen area. An analysis of the sensor data is then done and finds that on a statistically significant number of independently detected stress events, a combination of dynamic on-board indicators also highlights these events with a reasonable degree of accuracy.

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1. Introduction

1.1. Background

Cycling has been touted as a sustainable urban transport alternative to the automobile in recent years, as it is considered an efficient and accessible mode of transport (Pucher and Buehler 2017). However, the share of cyclists still lags far behind the share of drivers in Germany.

Recent research has found a significant impact of subjective, and, in particular, negative experiences, on the likelihood of adopting active modes like cycling. This confirms the presumed concept of an attractive infrastructure, wherein a large part of trips could be cycled, but are not done by bicycle due to concerns of safety and comfort. Transport planners have as a result aimed to find “problem areas” where these concerns are most pressing, which has spawned studies that measure rider stress to map into hotspots. Following the principle of risk homeostasis, stress arises from situations where a mismatch exists between the cyclist’s appraised level of risk and the baseline risk accounted for (Trimpop 1996). When a cyclist has detected enough risk and danger, a reaction should be taken to minimize risk exposure; and, as result, steady state cycling dynamics will deviate. Similarly, physiological markers will appear. Compact on-board computing, sensor technology and wearable health monitors have allowed the field of naturalistic cycling analysis to grow substantially in the last 10 years. Additionally, advances in consumer-grade e-bikes meant that these require and have access to ever more powerful sensors as part of their control and drive units. Bosch E-Bike is a manufacturer of pedelec motors and components and is creating new safety solutions for cyclists such as anti-locking systems (ABS) and B2X (bicycle-to-everything) connectivity. This study falls within the scope of B2X research on active safety in cycling.

1.2. Goal

Although cycling is a very intuitive and dynamic mode of transport, due to the coupling of the rider and the bicycle as almost an extension of the former, the link or parallelism between kinematics and physiological states still have not been considered in depth. Since a large part of cyclist accidents occur alone on the road (Schepers et al. 2015), and most accidents can be attributed to infrastructural issues as well as failures of control, it is beneficial to establish a method of finding areas and situations where the infrastructure may be causing discomfort for the cyclist with limited sensor availability. As minor single cyclist accidents are still underrepresented in statistics, and near misses are not counted in these statistics, this method may aid in reducing the blind spot in common incidents that are causing danger and discomfort and discourage bicycle use and adoption but yet are not visible in data available to planners.

The objective of this thesis is to detect instances of risk and danger and tie together physiological indicators of stress with cycling dynamics that can be collected from an instrumented bicycle with varying degrees of sensor availability. The research question being posed is the following: Which sensors, indicators and thresholds can be used to identify instances of stress tied to traffic conditions and cycling infrastructure?

The use cases for such a model of stress and data collection method are diverse; first, it can be used to identify common points of conflict and adjust warnings or navigation accordingly. Secondly, it can be used to generate rich geographical data for research and planning purposes. Finally, based on common patterns of handling in certain areas, it can also be used to improve path prediction and aid active safety systems in anticipating user reaction, which on a bicycle, unlike a car, cannot be ignored or overridden by electronic control systems.

1.3. Thesis Structure

The thesis is structured as the following: Chapter 2 will give a literature review of existing research and the state of the art in cycling and stress sensing, as well as studies that form the basis of the methodology of this thesis. Chapter 3 will give an overview of the methodology with indicators of interest that were selected and the basis of their selection, and then will cover the experimental setup and instrumentation to record these inputs. Chapter 4 will discuss the results, the analysis process and its implementation, and performance parameters and will dive into a critical reflection of the methods. Chapter 5 will synthesis the findings and contributions of this thesis and discuss possible improvements and developments.

2. Literature review

Having established the importance of cycling in transport strategy in section 1, this section will cover the current state of cycling research in the relevant areas of mode share, safety, dynamics and subjective perception, as well as texts that form an important basis for this thesis.

2.1. Cycling mode share factors

Research on transport and mode choice models have found that most often, the determining factors of mode choice are travel time, relative cost with income, waiting time, combined with subjective aspects such as comfort and enjoyment of the mode (Ben-Akiva and Bierlaire 1999). In Germany, cycling still lags far behind driving a car in mode share (infas Institut für Sozialwissenschaft 2022).

Incorporating subjective feelings of safety and physical effort, one can draw more nuance on why cycling is sometimes, albeit the practical option in combined costs, ignored in favor of other modes: Vos et al. (2019) found that enjoyment of travel has a reinforcing behavior on the mode choice. As such, first experiences with a mode can also highly influence the subjective perception of the mode in future choices, as positive experiences with cycling will likely encourage future cycling, and negative experiences will do the opposite. This highlights the importance of a forgiving infrastructure that allows for beginners to experiment with cycling without being subjected to extreme stress, in order to encourage a modal switch. This view is also shared in the CROW cycling design manual (Groot 2016). Cycle friendly infrastructure, such as separate cycleways and low speed limits in mixed traffic, is also stated to encourage mode shift in favor of cycling (Majumdar and Mitra 2019; Rayaprolu et al. 2020).

2.2. Measuring comfort

Although comfort is considered difficult to measure, there have been several efforts to quantify it in objective metrics so as to assess the ease of use of the cycling infrastructure. Hull and O’Holleran (2014) focused on how the infraucture allows or impedes movement, specifically in terms of exertion and energy. They considered that comfortable infrastructure is that which is smooth, flat, and presents minimal inclines. Agrícola et al. (2017) found that cycling at a cadence of 60 revolutions per minute (RPM) left cyclists with a significantly higher pleasure rating than at 100RPM. In the CROW manual, Groot (2016) similarly considers 50-70RPM as the normal range for cadence, wherein a slope that requires a higher cadence for a period of time does not conform to the design standards.

Mekuria et al. (2012) took stress as the counterpart to comfort and established the method of Level of Traffic Stress (LTS) which categorized road sections by the demographic that would be comfortable riding on them, with LTS 1 being the most accessible for even beginner cyclists, and LTS 4 being only usable by a small minority that is dedicated to cycling, the "Strong and Fearless" (Geller 2006). In the CROW cycling design manual (Groot 2016), comfort is measured in instances of nuisance per unit of distance in the network. Nuisance can be low speeds, interruptions and needing to stop, instances where overtaking is not possible, significant turns, and so on. These two sources are the conceptual basis for the definition of cyclist stress that will be used throughout this thesis, where it relates to the balance of safety and control ability.

2.3. Cycling safety

Indeed, perceived safety is often cited as the key obstacle to bicycle adoption (Hull & O'Holleran, 2014). In recent years, Intelligent Transportation Systems (ITS) have aimed to curtail the risks to automobile passengers as well as vulnerable road users. Cyclists however present a unique challenge for these systems as they relatively fast and unpredictable in their dynamics, especially as this can be affected by the cyclist's state of mind in reacting to a hazardous situation, which is more severe for less experienced riders.

Incidents involving an automobile are the leading cause of death for cyclists (EU Directorate-General for Mobility and Transport 2021). Bíl et al. (2010) conducted a statistical multivariate analysis and found that the most common serious incidents involving a car driver and a cyclist were, in order of fatality rate, those related to speeding cars, car driving style, overtaking manoeuvres, and cyclist riding style, respectively. It was also found that drivers were at fault most often, and that incidents that occurred at night were more serious on average. Dozza et al. (2016) found that e-bike riders tend to have more conflicts with motorized vehicles overall, and that the rate of conflict is strongly correlated with rider speeds. They also found that motor vehicle drivers present the largest threat and conflict cause for e-cyclists, in contrast to regular cyclists, who most often are in conflict with pedestrians, likely due to the higher speed of e-bikes that promotes using the carriageway. Kaplan and Prato (2013) conducted a clustering analysis of crash data in Denmark and found that 80% of crashes occurred at road intersections, commonly with right turning vehicles, especially heavy vehicles, suggesting that the cause of right-turn crashes may be blind spots, which are larger for those heavy vehicles.

2.4. Cycling dynamics

To better understand cyclist behavior and how they handle their bicycles, Dozza and Werneke (2014) created an instrumented bicycle setup that served as the inspiration for the setup used in this thesis. Using that setup, they found that several inputs could be measured, such as inclination, cadence, speed, handlebar angle, braking force, examining self-reported conflicts and crashes. It was found that risk of crashing was significantly higher when the road is poorly maintained and when crossing intersections. However, these findings were based highly on self-reported incidents, with the data collected from the bicycles themselves only serving as a contextual aid, as too small a number of conflicts occurred and there was not enough data to link kinematic data to less severe conflicts.

Due to their dynamics, cyclists are also harder to predict than drivers, which increases the chance of drivers misjudging the road situation. Westerhuis and de Waard (2017) posit that for most cases, inferring the intention of a cyclist by observing them is difficult, but that certain cues do exist that can be used to implicitly predict their intentions with better-than-average probability, based on the rider’s head movements, orientation, and speed. Pool et al. (2017) have found that integrating road network data and topology into a dynamic linear system model of a cyclist can be used to improve the accuracy of path prediction by around 20%, especially for sharp turns. Pool et al. (2019) also propose a recurrent neural network based system that combines sensor data with environmental map data. Sensors detect object context cues to make more accurately predict a medium-term path as a probability density field of spatial points. This performs better than previous implementations such as Dynamic Bayesian Networks or Linear Dynamic Systems. Lee et al. (2020) also found that the obstacle avoidance maneuver, a critical reaction in conflict scenarios, also takes the form of a Gaussian-like curve in displacement, having also parameters for its duration and width.

These findings contributed to the establishment of indicators that signal a change of intent on the part of the cyclist.

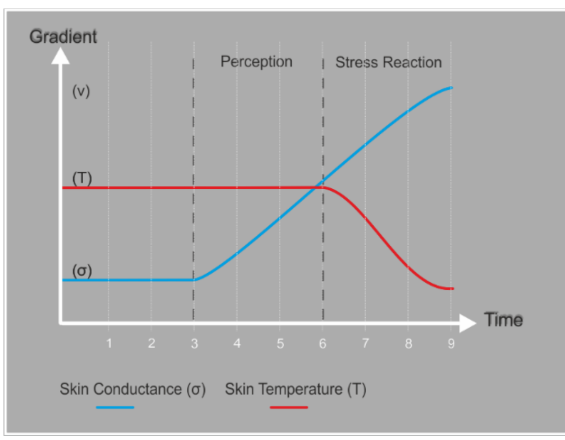
2.5. Perceived danger and dynamics of driving

The risk of collision with an automobile and risk perception have also been found to play a key role in riding behavior, and these make cyclist actions even less predictable. Rowden et al. (2011) found that stress from road conditions has negative impacts on reaction times and decision making and causes a higher rate of accidents.

Llorca et al. (2017) analyzed perceived risk in cyclists during overtaking maneuvers and found that clearance was secondary to the nature of the vehicle overtaking, in addition to speed, which was more significantly correlated with high perceived risk. However, a large element of the perception was subjective, and significantly depended on the cyclist reporting the situation. Matthews et al. (1998) established a methodology to assess (automobile) driver stress in relation to driving skill and reaction to critical events. They found that younger drivers tend to be more aggressive and less frequent drivers, and that aggressive drivers tend to be less skilled. However, it was also found that stress is not directly related to driving skill, as reactions to the stressful stimuli are variable, ranging from cautious behavior to aggressive driving. Therefore, reaction to stress is also dependent on factors such as age and skill.

2.6. Measuring physiological stress

To overcome the challenges of subjective stress rating and variable stress response, psychologists have also devised methods of measuring stress via physiological markers. Sano et al. (2018) have found that wearables can be used to measure various physiological phenomena and measure, with 79% accuracy, the user's level of stress. The most sensitive factors were skin conductance, heart rate variability, and blood pressure. Caviedes and Figliozzi (2018) also conducted an experimental study and found that these measured physiological markers can be traced to stressful incidents on the road, and offered a viable method to measure them in real time and account for delayed stress responses. They found that traffic conditions and road infrastructure significantly impacted stress markers. The stress/road-condition relation could also be have a feedback element, where stress can create or exacerbate unsafe conditions, as in the automotive field Ritter et al. (2007) have found a relation between degraded driving performance and measured stress. Kyriakou et al. (2019) and Zeile et al (2016) studied stress response for cyclists and pedestrians equipped with GPS tracing, and found that locations can be correlated with stress data for cyclists and pedestrians, suggesting the existence of stress hotspots where conflict is likely to happen.



Seconds	Electrodermal Activity	Skin Temperature	
1	0	0	Normal Move
2	0	0	
3	1	0	Perception
4	1	0	
5	1	0	
6	1	-1	Stress reaction
7	1	-1	
8	1	-1	
9	0	-1	
10	0	-1	

Figure 1: Stress Response Measurement according to Zeile et al (2016).

3. Methodology

The methodology incorporates experimental elements from Dozza and Werneke (2014) and Zeile et al. (2016), along with concepts from aforementioned studies and guidelines from the FGSV and CROW manuals. The methodology followed was primarily focused on detecting stress and indicators of conflict to study their possible correlation.

The research took the form of a semi-naturalistic in order to realistically study riding patterns in different contexts and conflict situations and find relations between sensor data and physiological states. To balance the requirements of repeatability and data reliability, the following strategies were used and will be described in detail in subsequent sections.

3.1. Experiment Design

The semi-naturalistic experiment was selected in order to observe organic traffic conditions, as a controlled environment could not be guaranteed to cause an accurate stress-response nor would it be feasible to cause such a response without putting participants at risk.

3.1.1. Test Route.

The study area in question is the area around the Bosch eBike campus. For the naturalistic nature of the experiment, this area provides a variety of bicycle infrastructure sections and different possible interactions types with road users. Within the area are the two cities of Reutlingen and Tübingen, covering around 22km^2 and 23km of cycle paths. With slightly more than and less than 100.000 inhabitants respectively, the two cities of Neckar-Alb region are middle to large in population size.

With a mode share of 9% for cyclists and a ADFC cycling score of 4.19 (ADFC-Fahrradklima-Test 2023), Reutlingen’s cycling infrastructure is lacking compared to similar-sized cities of Baden-Württemberg which on average have a mode share of 15%

for cyclists and an average ADFC score of 3.97. This difference is especially stark with Tübingen's score of 3.32. This indicates that the area is probably slightly more stressful to cycle in than in most medium-sized cities in the state and is therefore an interesting testing ground for stress measurement.

A designated section of the road (Fig. 1) was selected in order to obtain consistent, aggregated results that speak of the cycling infrastructure to avoid overrepresenting single occurrences that may be outlier events. The route that was chosen combined diverse traffic conditions and convenience for participants. The route included long-distance cycleways, urban bike lanes, mixed traffic sections, and areas with heavy vehicle traffic, which is also expected to cause more stress (Llorca et al. 2017). The route was also evaluated according to the LTS criteria in anticipation of possible stress hotspots (Figure 1).

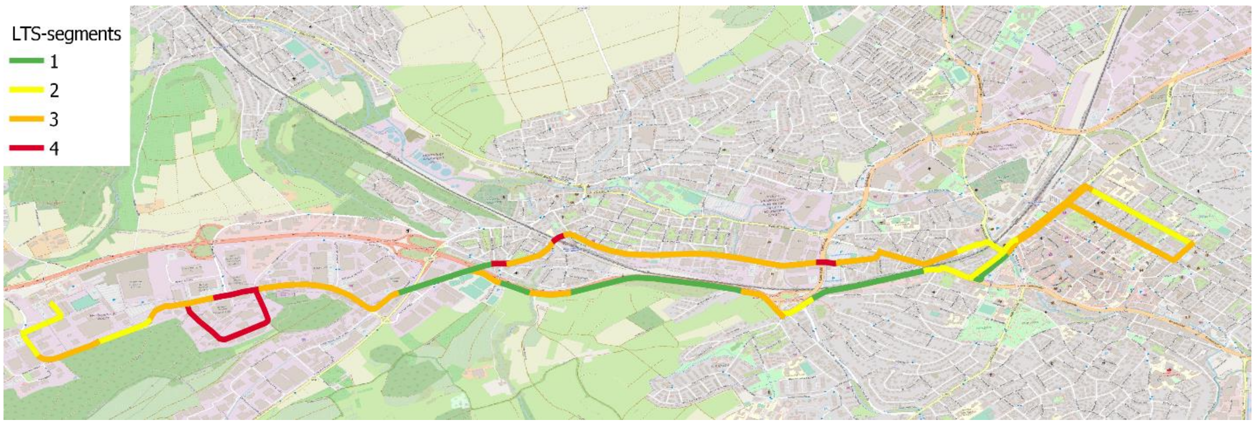


Figure 2: Level of Traffic Stress by segment.

3.1.2. Experiment Procedure

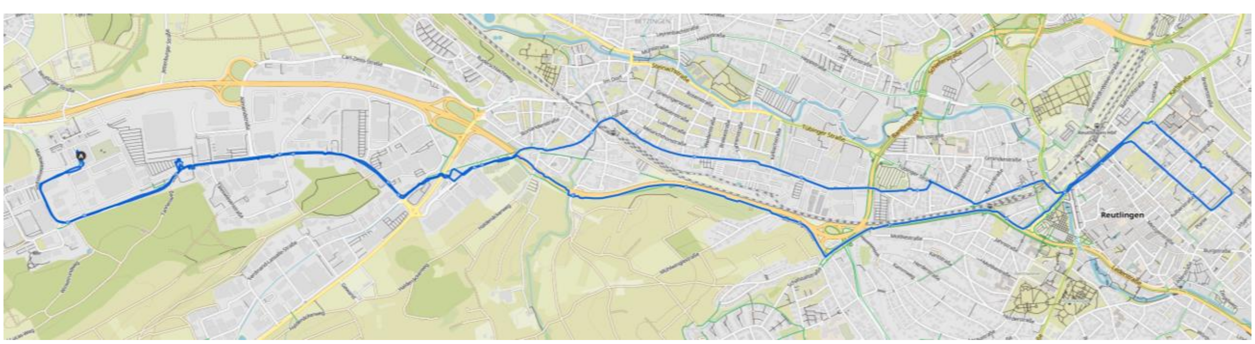


Figure 3: Map of the fixed daytime route from the Bosch eBike Campus into Reutlingen center.

A short questionnaire was conceived to collect information about the participants (skill level and confidence) and their preferred ride times and routes. It was accompanied by a form (Appendix B.1) explaining the nature of the experiment, what will be collected, and how data is handled, alongside an agreement to the conditions of data processing. It also clarified that in all cases, any case of injury while riding is treated as work-related.

Employees at Bosch eBike (EB) had the chance to take part in the study:

- By riding a defined route during a specific time during the workday.
  This gives us more reproducible data, with the same track and times of day for riders.
- By riding back home and returning with the Ebike the next day.
  This allows us to see traffic at more interesting times like rush hour, for which we would have difficulties otherwise finding volunteers available before/after regular work hours. Additionally, we can compare stress levels from habitual rides vs new environments.

Each participant was given a randomized participant ID to maintain anonymity.

Participants were given a bike suitable to their height and were equipped with the smartwatches. A “feel” test was conducted to make sure they are comfortable in the saddle and know how to operate and where to find the gear shifters and bell.

The test procedure comprised the following steps:

- Starting data collection on the NUC.
    - Done by running the *data_collection.sh* script to start CAN nodes and the python file *new_arduino_save.py* and entering the participant ID, watch used, and bike number.

- Connecting smart watch.
- Preparing iPhone navigation and multisensor app.
- If they are unfamiliar with Ebikes or the FOCUS 2 model, test lap around surrounding area was undertaken.
- Starting GoPro recording.
- Starting sensor and watch data collection on iPhone.
- Riding the route.

These steps are then followed in reverse to stop the recording. Since iPhone data is more difficult to segment (clock accuracy) and it has the least amount of available memory and battery it's prioritized to make sure the file is saved and sent correctly.

Amendments:

Following a road incident resulting in an injury, the procedure was amended to include the following steps:

- Accompanied ride for first timers.
- Practice lap for all participants.
- Daily road inspection.
- Warning about bike's dynamics in specific maneuvers in difficult weather like rain or snow.

Following mislabeled data, and corrupted files especially in commute rides where the rider did not stop the collection or turned off the bike upon arrival, we also implemented a file naming standard for all generated files and automatic saving functions. We also included an instruction sheet in the storage space for commuting riders. Relaunching data collection was simplified to happen in a couple of key presses with automatic detection of the correct USB ports for CAN and Arduino, due to the lack of a suitable screen.

3.2. Instrumentation

To generate the quantitative data that is needed, a dedicated, custom hardware setup was created on two trekking e-Bikes. These were two FOCUS Aventura2 bicycles with a large (henceforth referred to as Bike 1603) and a medium frame (henceforth referred to as Bike 1595). This setup integrated existing sensors with new ones outfitted for the purposes of the experiments. Since it was not known which dynamic and external factors can be correlated to stress, the instrumentation strategy was to cover as many indicators of cyclist state and behavior as possible.

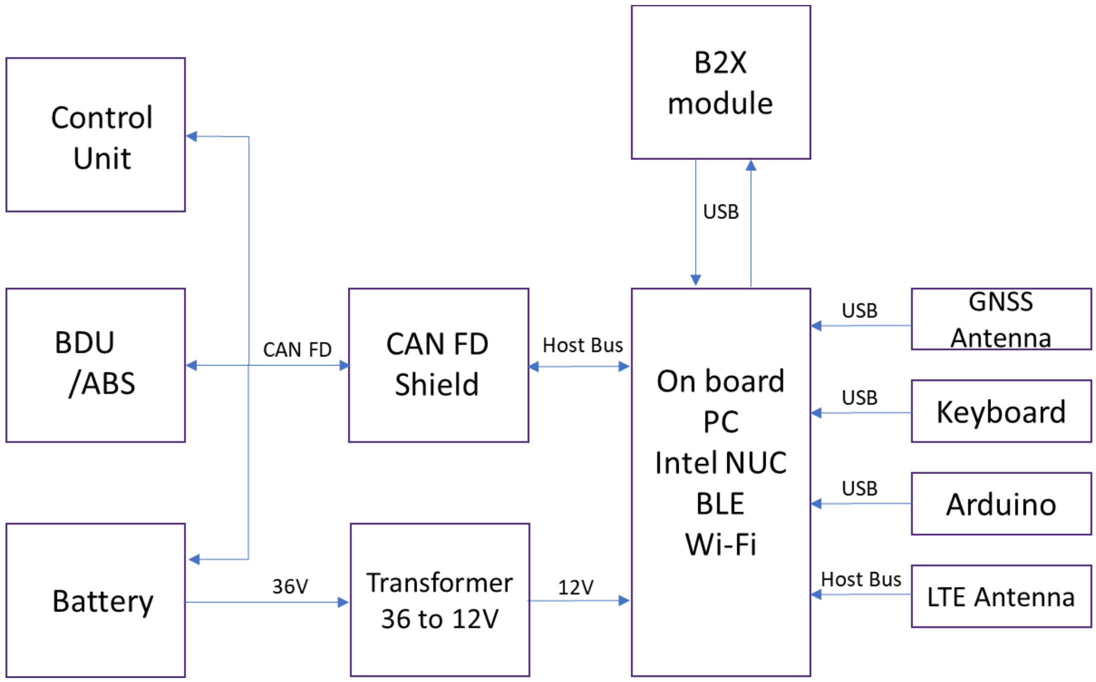


Figure 4: Hardware setup flowchart.

Figure 5: On-board computer setup.

In order to determine the best setup that can achieved minimally and scaled up, several levels of sensor combinations are defined, from the most basic, to the most complex, which are described in the following table:

Table 1: Sensor Availability Levels.

Sensor Level	**Sensors included**
L1	Drive Unit (IMU, speed, cadence)
L2	// // // + ABS
L3	// // // + Bell Sensor
L4	// // // + Handlebar usage
L5	// // // + Head turning detection

The experiment used the depicted (see figure) data flow from sensor systems in the data collection setup, which will be described in this section in detail:

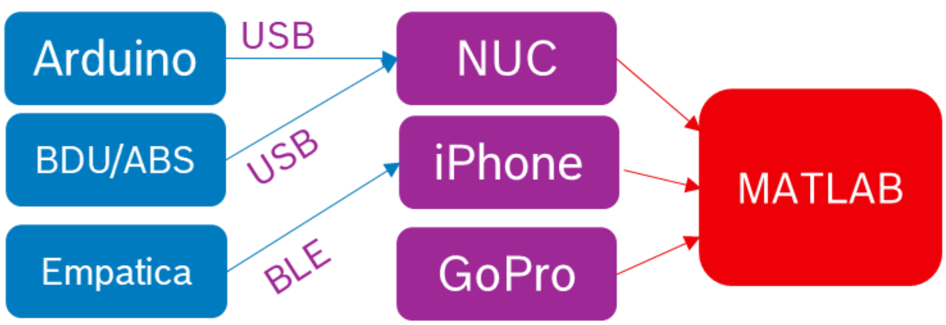


Figure 6: Data Flow Chart.

3.2.1. Bosch Drive Unit (BDU) and ABS with development firmware:

The BDU is set to transmit all CAN messages which are used internally or for debugging purposes. The Bosch ABS is mounted on the brakes, it is also sharing all debugging messages.

These two units are connected via a splitter, SUB-D 9-pin to a CAN interface. The latter is connected by USB to the Intel NUC mounted on board. CAN Messages are recorded by the LinuxCAN library in a BLF format at the end of recording. The file carries a timestamp of the time of creation, but the messages themselves have no timestamp, only absolute time delta between messages. Together, the two units give access to inertial sensor data, odometry, and torque, and braking pressure measurements recorded throughout the rides.

3.2.2. Arduino Sensors:

An Arduino board connected to waterproof capacitive sensors adapted to detect hand placement on the handlebars (Bike 1603) and on the bell ringer (Bikes 1595 & 1603) by transmitting changes in capacitance from human skin. The setup uses copper tape to extend the detection area of the sensor. By having the adequate copper tape length and thickness these extensions are used to create a contact point that is minimally intrusive without affecting the sensor readout itself. This is achieved by the fact that the copper tape has similar enough conductive and dielectric properties to the sensor contacts to not substantially alter the charge stored in the capacitor on its own, but can conduct this charge to the rider’s hands and thereby trigger the sensor.

In winter conditions, gloves may be needed. Depending on their material, these can either block or still maintain the sensor’s sensitivity. Before each ride, these are tested and if necessary, copper tape is also added to the gloves at common grip points to detect contact. The additional surface of copper tape creates enough of a dielectric difference between states such that the contact is also detected as a touch.

This sensor is also connected to the NUC via USB. Using a python script, simple encoded messages from serial ports are monitored timestamped and periodically added to a CSV file. In order to not overload the serial bus with several concurrent messages, the signal is summarized in a single integer with the following formula:

$$state = RHB_{filtered} * 2^0 + Bell_{filtered} * 2^1 + LHB_{filtered} * 2^2$$

Where LHB and RHB are “left handlebar” and “right handlebar” respectively.

3.2.3. iPhone:

The iPhone mounted on the handlebars also collects some data. Via the Komoot app, we have navigation information displayed and GPS history is collected. With an application with access to the Gyro/IMU sensors, the pitch, yaw, and roll of the handlebars are also saved. These values have been calibrated via a disc fitted on the frame with angles annotated as ground truth.

3.2.4. GoPro cameras

Two cameras are mounted. One of them faces the road and serves to cross-reference detected events with actual occurrences on the route. The audio track is also extracted to detect bell ringing. The other camera faces the rider and records their face's movements. This is later used to analyze shoulder glance behavior.

3.2.5. Empatica watches:

These specialized wearables measure physiological data. The data used for stress detection is the skin galvanic response, heart rate variability, and skin temperature. The watches have two modes of recording the data:

- The E4 model connects to an app which records the raw values in a SQL database file.
- The Embrace model connect to an app which records the raw values in an AVRO file and also provides minute by minutes processed values.
- Data is timestamped in date/time and unix time.
- Both watches have inertial measurements which were used to validate corresponding timestamps with the bike's measurements relative timestamps.

The watches were worn on both hands to minimize dominant hand effects on Galvanic Skin Response (GSR).

Watch data was also processed by Dr Peter Zeile of the Karlsruhe Institute of Technology to determine stress points. This was determined with changes in GSR and skin temperature and heart rate.

3.3. Indicators

To measure rider states through physical indicators, we have the following key indicators of state:

3.3.1. Braking [2]

With the risk of falling over, cyclists are reluctant to brake hard. As a result, strong braking is likely to indicate a dangerous road situation where a greater risk exists.

a) To differentiate between varying levels of intensity, only braking pressure above 60psi is highlighted. Lower intensities would occur from minor, controlled deceleration.
b) Braking while stationary is ignored.

3.3.2. Accelerations [1]

High values of acceleration/deceleration that go beyond comfort ranges stated in the CROW manual (2016) are highlighted. For most cases, high forward deceleration is undesirable and signals a disruption. In the Z axis, high acceleration causes energy loss and sustained cyclic vibrations can also reduce visual perception (Ishitake et al. 1998).

3.3.3. Speed [1]

Very low or very high speeds result in difficulties in controlling the bicycle (Groot). Low speeds are assumed to be a limiting factor from the environment or traffic situation as instability is undesirable to cyclists.

3.3.4. Cadence [1]

High cadence over longer times can signal exertion and steep slopes. When sport is not the objective, such as in a pleasure ride or commute, this can cause fatigue and frustration and result in stress.

Cadence discontinuity, sudden reduction to 0RPM indicates a need to observe upcoming road conditions better, be more visible, and increase potential time to collision (TTC).

- Since Pedal assist turns off at speeds >25km/h, instances where cadence drops around this value are ignored since they are often not a reaction to the environment but part of individual effort/energy management strategy.

3.3.5. Lateral maneuver [1,4]

High, oscillating acceleration laterally shows a fast displacement and realignment, which could be an avoidance maneuver. A wave-like acceleration is assumed as the rider would lean and turn into a direction to avoid an obstacle or vehicle and then lean and turn into the opposite direction to recorrect course. Quick maneuvers, with less distance and time to react, will result in a noticeable amplitude in a certain frequency range. This movement creates a higher frequency acceleration waveform than a normal maneuver executed under comfortable conditions, since we assume, the rider would avoid strong maneuvers both to maintain their balance and to be more "readable" to other road users.

3.3.6. Bell usage [3,5]

Bell ringing implies a dangerous road situation occurred or is about to occur according to the assessment of the rider.

Bell preparation (finger on the bell in a ready state) implies the same situation, but a lesser degree of intensity where such a level of danger did not go over a certain subjective threshold.

3.3.7. Head turning [5]

Head turning and shoulder glancing can signal anticipation of possible conflict, where the rider must evaluate if the manoeuvre they are about to perform or another road user might perform can be done safely from where they are.

3.3.8. Stress Peaks [6]

Galvanic skin response (GSR) signals arousal of nervous system in reaction to environmental stimuli.

A decrease in skin temperature indicates blood recirculation towards the core as a reflex response to danger and potential injury.

[1]: Measured by BDU. [2]: Measured by Bosch ABS.

[3]: Measured by Arduino Sensors. [4]: Measured by iPhone.

[5]: Measured by GoPro cameras. [6]: Measured by Empatica Embrace/ E4 watches.

Not included –but considered– were the following sensors:

- Handlebar angle sensor: This sensor was initially tested with a modified automotive sensor but not installed due to compatibility issues with software and hardware as it interfered with frame components and cables.
- Temperature, rain, and wind data: Although significant factors of rider safety and comfort, the variability of these elements on a precise scale renders comparison impossible due to the small scale of the data collection. A coarse level of information was instead adopted, where weather conditions were described as *dry, wet, rainy, snowy/icy*. Temperature was deemed to be less significant, and wind could not be easily measured as the riders' bearings would change throughout the ride, and reconstructing wind conditions from weather data after the fact would be difficult.

3.4. Data Processing

3.4.1. Data Cleanup

The collected data is not immediately usable for analysis after saving. It must first be restructured and adapted in Vector CANoe to be readable by the MATLAB processing algorithm. Data received from the CAN interface is then converted into a MATLAB Matrix and the absolute timestamp marking the start of recording is then added to each measurement timestamp, as the CAN files measures time 0 as the start of data recording. This initial absolute timestamp is provided by the Python module running in parallel on the NUC and recording the data from the Arduino when the script is started.

Similarly, timestamps from the GoPro must be extracted from the metadata. This is done in a JavaScript console with functionality available from gopro-telemetry. The outputted JSON file is then read in MATLAB and converted into a matrix.

Data from the Empatica watches is also converted into readable MATLAB readable formats. A Python script was created to convert and process data from the SQLITE and AVRO files into filtered arrays with moments of stress.

Additional, manual cleaning of the data must also be done in some cases. For cases where the participant ID was not entered, the schedule and video files when available are referred to determine which participant was riding which bike. Due to pairing errors, the watches may sometimes pair to a phone bearing a different ID. To verify correct association of the data, IMU plots are compared for the watch and the E-Bike and should mostly be matching when the watch's data is correctly associated to the E-Bike's data. In some cases, the handlebar sensors would lose contact due to the copper tape on the gloves crumpling. This is inspected visually and in suspected cases the touch sensor input is discarded for the unreliable sensor(s). Rides for which essential data is correct and available (Watch Data & Sensor Data) are grouped into subfolders where they are processed. Cases where the watches were not worn or connected properly altogether are discarded.

3.4.2. Signal Filtering

To be able to compare data from different streams, signals need to be synchronized and the indicators must have a unified, consistent sampling that facilitates matrix operations in the processing state. This is done through the following:

· Data streams are synchronized according to common event points.

  - This is done by detecting the start of the ride after the “warm up” tour and subsequent halt, which is visible with GNSS data on the phone, and IMU data on the bike and watch.
  - From that point, the start and end point are determined interactively by visualizing this data and clicking on the graph in MATLAB. Once the signals are synchronized, they are then converted to a common timeseries with a specific sample frequency.

- Indicator values that are dependent on other contextual values (braking or inclination while stationary, cadence reduction when 25km/h is reached) are adjusted by multiplying the value vector with a binary conditional vector.
  - For example, from instances where the speed is near 0, a “Standstill” binary timeseries is assigned values 0 and 1 (see figure). The result would be that IMU data for example, which would show high values when standing since the cyclist would be inclined on one foot to one side, are instead zeroed to keep this state from affected indicators.

- The sample frequency used was 40Hz as most sensors were operating in similar or lower frequencies. The exception is the IMU which operates at 1000Hz, and where vibration data would be lost if immediately resampled at 40Hz since road vibrations that affect user comfort and perception can go up to 80Hz ilato and Petrone 2012).
- For IMU signals, vibrations are measured first as amplitudes in a bandpass filtered timeseries, thresholded, and then resampled to 40Hz.

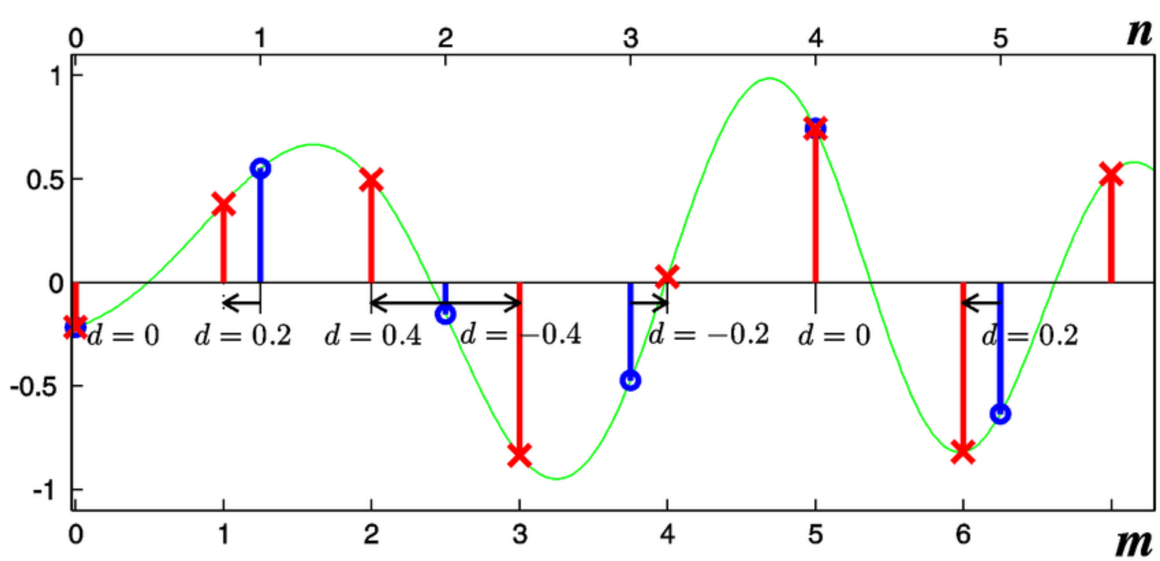
Resampling is necessary in order to combine indicators into a single equation along a common timeframe. A lower common sampling frequency also improves computation performance.

Resampling occurs according to the following principle:

- Time range is divided into even measurement times/ticks known as *unit blocks* such that the block occupies the time range of the timestamp ± Sampling rate/2.

- If there are measurements within a unit block, they are averaged together to obtain a single value per block.
- If there are no measurements within a unit block, these blocks are marked as skipped, until another measurement value is reached. Once reached, all skipped blocks are filled with interpolated values between the newest measurement and the last known one.
- This method provides a flexible solution for varying sampling rates and measurement

Figure 7: Resampling and interpolation. Author: Blok, Marek. (2012).



deltas, which is the case for many CAN messages when the bus is overloaded, or when the file size becomes large and read/write operations lag before memory is cleared.

Filtering and thresholding:

For most signals, raw values do not give much insight about the state of the cyclist and bicycle. Signals can also be related to the same dynamic event but have different response times to one another. To draw indicators from these values, we need to differentiate values and patterns from normal riding behavior. The following filtering methods are applied to each signal to get indicator values:

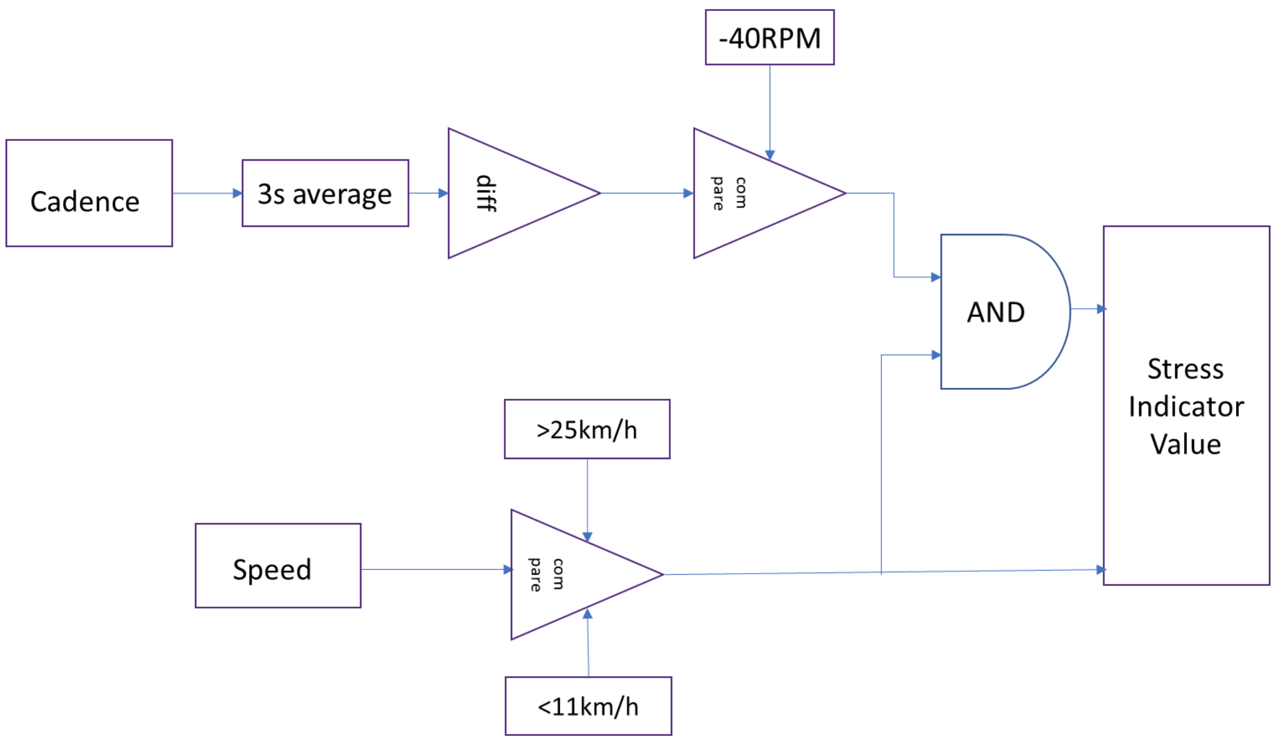


Figure 8: Example processing flow for indicator.

Table 2 : Indicators, interpretation and chosen value.

INDICATOR	TRANSFORMATION	THRESHOLD	COMMENT
STANDSTILL	Binary timeseries	Speed Below 0.2km/h	Used to zero other indicators that require motion as a condition.
SPEED	Binary timeseries	Speed Below 11km/h	
BRAKING	Filtered Value.	Over 60PSI	Zero below threshold, scaled value above threshold.
CADENCE HIGH	Cumulative value timeseries.	Over 85RPM.	The longer cadence is sustained over 85RPM, the higher the indicator value. Zeroed when it dips below 85RPM
CADENCE LOW	Binary Timeseries	Below 8RPM.	Time sensitive, Boolean true if cadence is below 8RPM for a duration of 1s or more.
LATERAL MANEUVER	Binary Timeseries.	Symmetrical Displacement over 30cm over duration of 0.8 to 3 seconds	See detailed method in “Lateral Maneuver Detection” section, 2.4.X
BELL USAGE	Binary timeseries	Duration of 0.5 to 4 seconds.	Shorter or longer averaged signals in time are considered as misdetections.

HEAD TURNING	Binary timeseries	Angle >±30^0	
VERTICAL VIBRATIONS	Filtered Value	0.25G	Zero below threshold, scaled value above threshold.

3.4.3. Lateral Maneuver detection.

A novel method using IMU motion patterns to detect specific avoidance maneuvers was implemented to find instances where cyclists swerved around an obstacle or road user, without stopping or significantly braking. From Lee et al. (2020) and Groot (2016) we know that cyclists tend to follow a straight line with some minor wobbling, with up to 30-40cms of later displacement, and that when faced with an obstacle, they tend to avoid this obstacle within a range of comfortable distance and time. The avoidance maneuver takes the form of a Gaussian function, whose parameters are the duration 2σ and the distance of the displacement α.

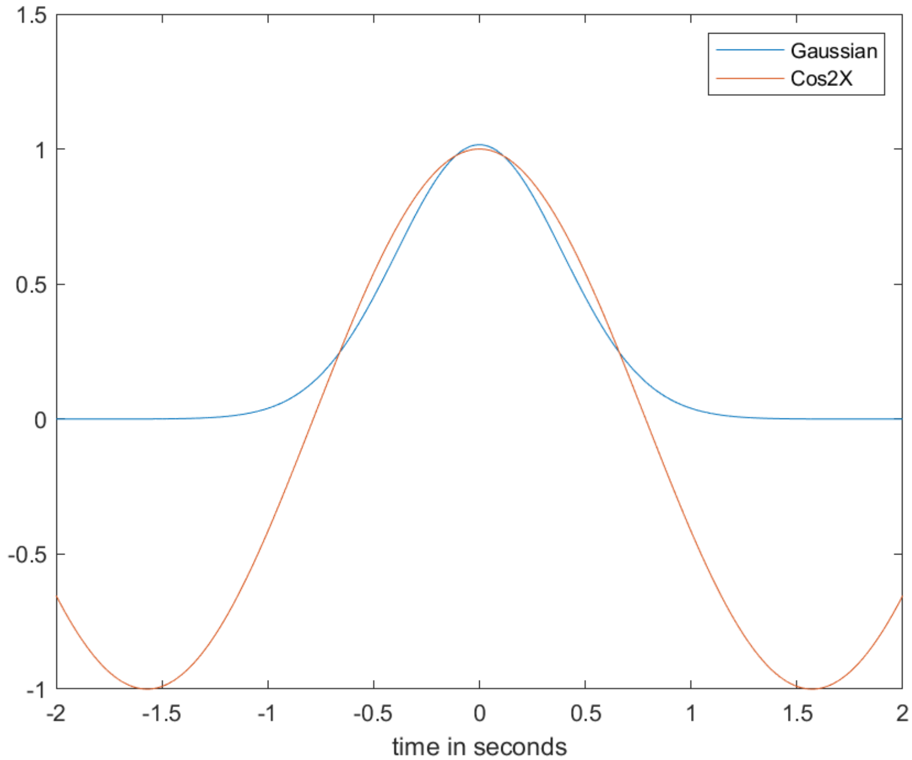


Figure 9: Gaussian Distribution versus sine approximation.

The second derivative of this function, acceleration, can be approximated with the sinusoid function $= -\frac{64}{\pi^2}\alpha \cos 4\sigma$. This approximation is accurate enough for a large part of the motion and covers the largest changes in amplitude around the peak.

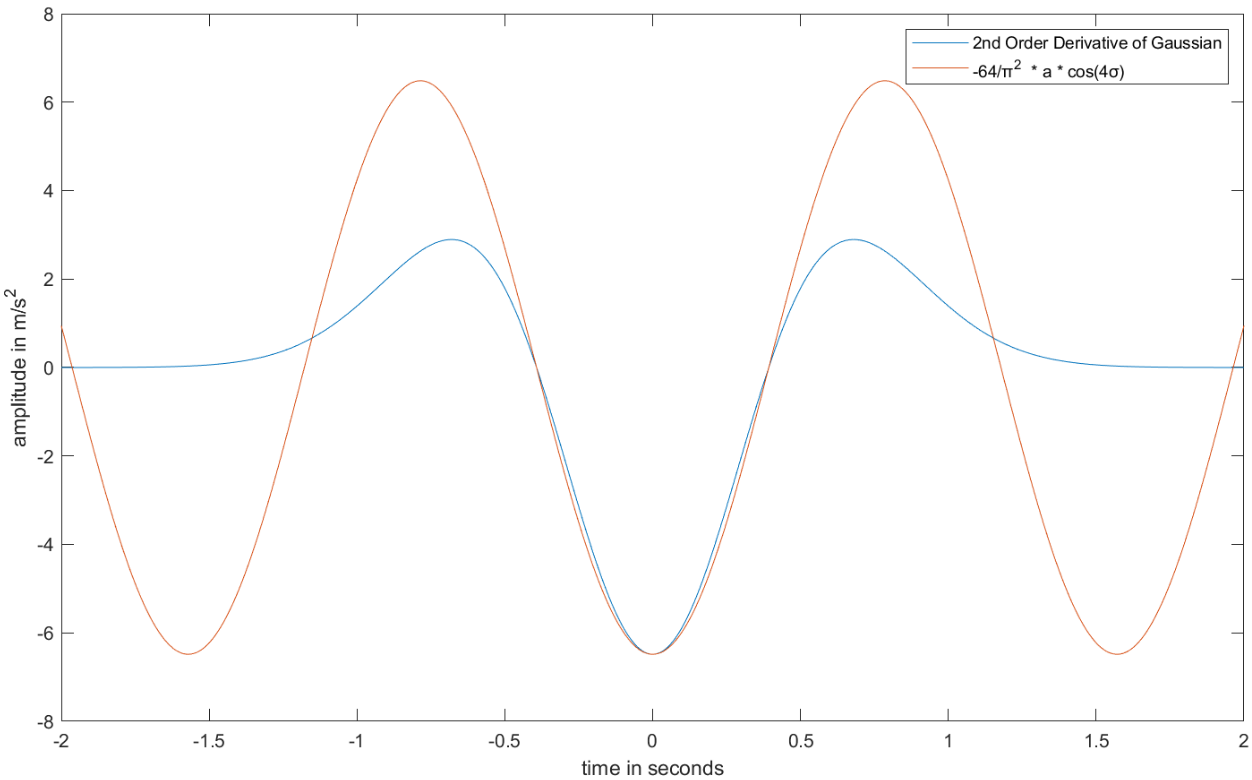


Figure 10: Second order derivative of the Gaussian versus its sinusoidal approximation.

This renders a simpler type of wavelet fitting possible via a bandpass filter. As amplitude α corresponds to lateral displacement and 2σ to the duration of the displacement, critical values for the second order derivative approximation also can be derived for critical values of α and σ, one obtains the thresholds for amplitude and frequency ranges:

$$2\sigma = [0.8\ 3.0s] = [0.\overline{3}\ 1.25Hz]$$

$$\rightarrow 4\sigma = [\ 0.\overline{6}\ 2.5]$$

$$\alpha = 0.4$$

$$\rightarrow -\frac{64}{\pi^2}\alpha = 2.59$$

With these bandpass parameters, detecting avoidance maneuvers is possible to some level of accuracy. This makes incidents visible, where no strong braking or where no foresight/cadence management is possible due to the speed at which it occurs, and makes the reconstruction of events more complete.

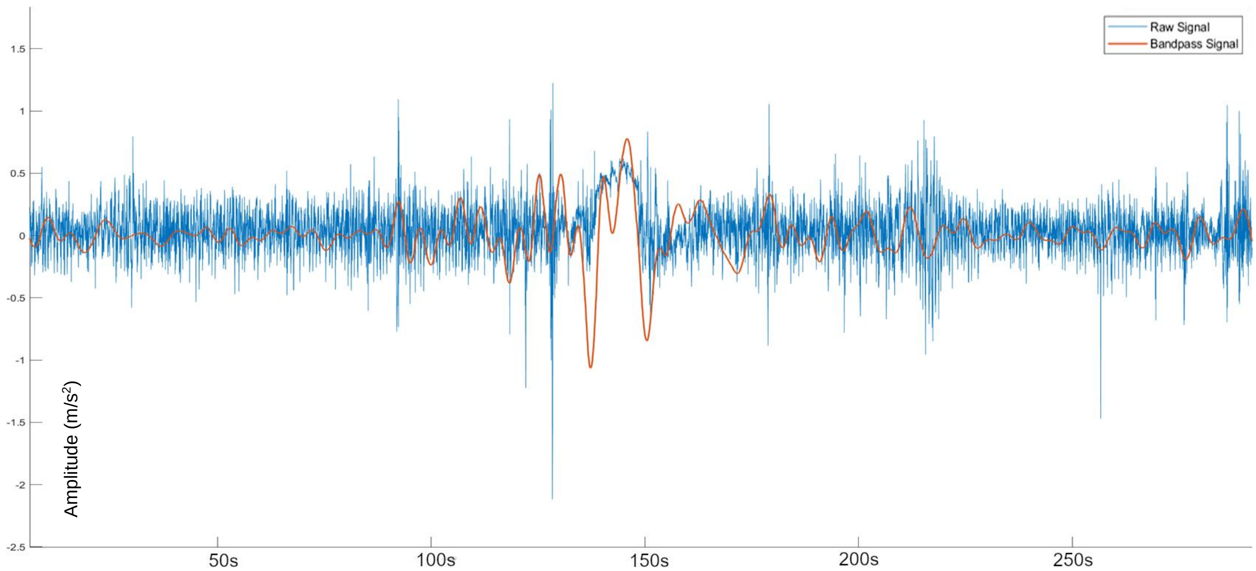


Figure 11: Raw vs Processed IMU Signal.

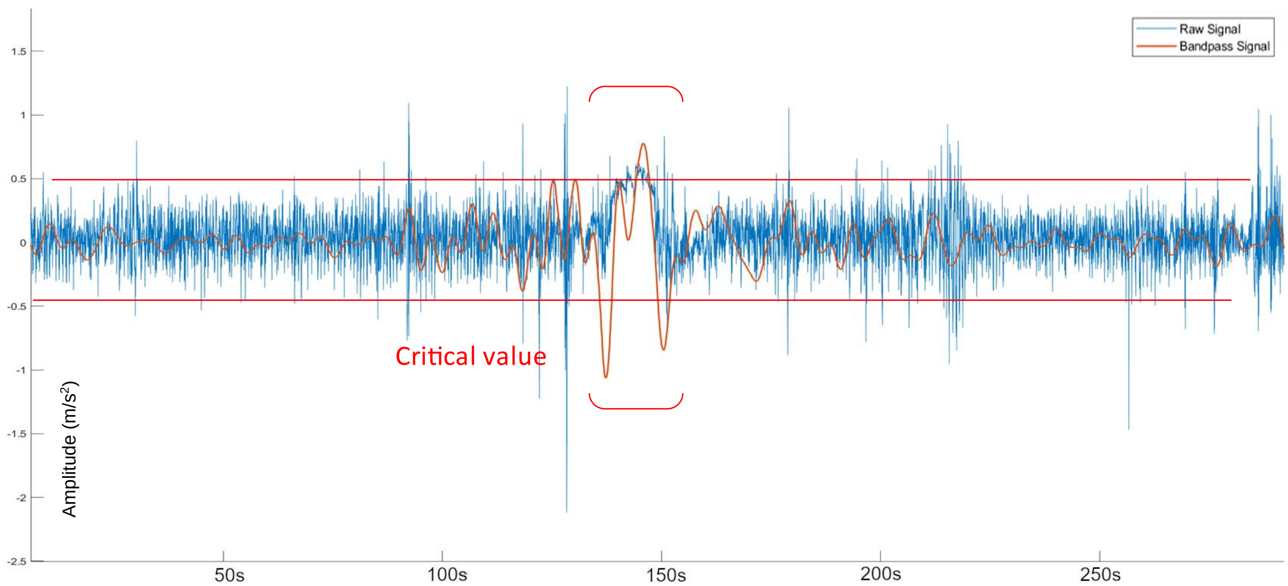


Figure 12: Threshold Applied to Filtered Signal.

3.4.4. Empatica Watch Data:

The Empatica watches output data at 1Hz to 400Hz depending on the signal. *Skin Temperature* and *Galvanic Skin Response* are the primary variables to detect stress. Because these raw values are affected by exposure to the elements and by environmental factors, they must also be filtered to provide more meaningful data.

As the experiment took place in winter, when insulation is inadequate, wind can cool the wrist area as wind enters it, especially at higher speed. To differentiate between temperature changes caused by cold air and temperature changes caused by a change in blood flow to the extremities, the indicator reacts to changes in the rate of change of the temperature.

Since GSR is also dependent on perspiration levels, as more humid skin conducts electricity better, it was also observed that this raw value tends to rise with time as riders sweat, especially if heavy winter gear and gloves are worn. Hence, to preserve the sensitivity of temperature sensing can also have the byproduct of affecting the GSR value. As a result, the GSR was scaled on a running average and strong changes were highlighted.

Due to materiel delivery delays, this was not used for all rides, and calibration was also imperfect by the end of the experiment. For moments of stress, as a reference, measurements and processing by Dr. Peter Zeile were used as they were available at the beginning of the data collection and were deemed more reliable and better calibrated.

3.5. Correlation Analysis Parameters

3.5.1. Indicator calibration and weights

Initial analysis shows a relation between stress peaks and braking and accelerations, but not so much for slope or high cadence. Some stress peaks also did not have any correspondence with indicators, until lateral avoidance indicators were introduced. However, visible already was the discrepancy in time between stress response and indicators peaks.

Initial thresholds used were based on values extracted from literature. Some values were adjusted to improve the sensitivity of indicators for the properties of the E-Bike and the track, such as critical cadence and exertion and slope.

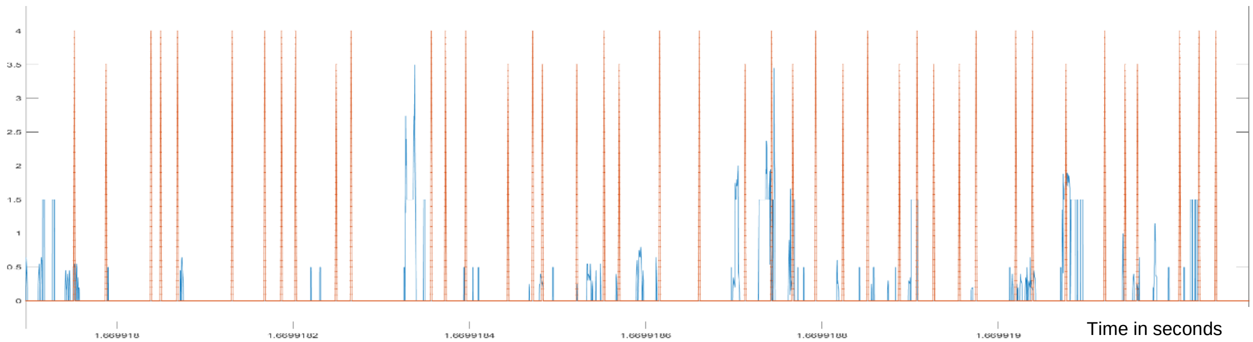


Figure 13 Initial indicators (blue) vs stress peaks (orange).

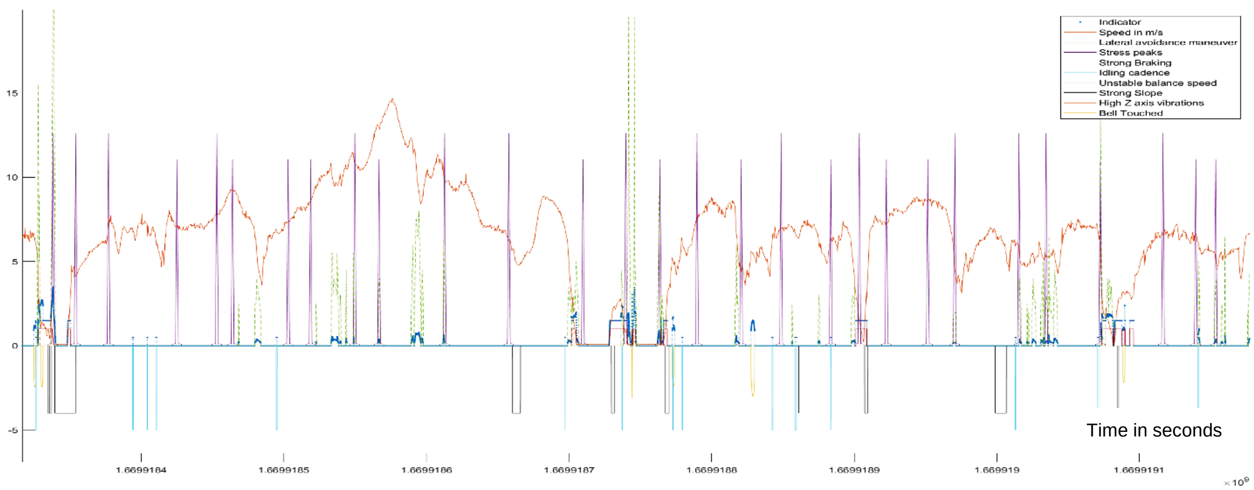


Figure 14: Improved model fusing additional data.

With more data from the handlebar sensors and bell sensor, a better model is obtained(Fig.14)

However, there is an apparent lag between the indicator peaks and the detected moments of stress. This in line with the findings by Zeile et al. (2016) and Kyriakou et al. (2019) who found that the physiological response may lag several seconds behind the actual stressor event. Zeile cited 8s as the average time for the response to be detected. The extent of this delay however varies from participant to participant, with different riders having different delays, however all were within the same order, of 5-20 seconds.

3.5.2. Cross-Correlation

To mitigate this and extract metastatistics about the model and its accuracy, a cross-correlation was performed on the indicators and detected moments of stress.

Cross correlation between two time varying functions is calculated with the convolution:

$$f * g = \int_{-\infty}^{+\infty} f(\tau)g(t-\tau)d\tau$$

where $t = time\ shift$ (Blackledge 2013).

This was accomplished by feeding in both time series into a function, given a range of time shift alongside a number of layers L and a number of steps S. The function iteratively maximises the degree of overlap of both functions.

Pseudocode:

```
NewRange=TimeRange

     For l going from 1 to L

          For s going from 1 to S

               Overlap(s)= sum(f dot g)

          BestOverlap= NewRange(MaxIndex(Overlap)

          NewRange=[BestOverlap-2/L  BestOverlap+2/L]

     Output(BestOverlap, Max(Overlap) )
```

This allows an optimal time shift to be found for each ride from which the degree of cross correlation could be computed and different combinations and weights of indicators to be evaluated and compared against each other.

To allow for a gradual and more lax optimization process, the binary signals are passed through a Gaussian kernel that extends an impulse peak to a Gaussian curve that peaks at the impulse but preserves positive values around the impulse in a range of ±1 second.

3.5.3. Variable time shift

However, while the result showed improved correspondence between measured stress and stress indicators, there also seems to be different optimal time shift values for different segments of the same ride. This is likely to be due to the previously mentioned temperature and GSR sensitivity changes as time progresses. The general trend is that the optimal time shift decreases as time goes on, which can also be due to the adaptation to the riding task as the rider becomes more aware of their surroundings after exposure to risks and repeated stimulus increases vigilance and reduces reaction time.

A possible solution which was adopted was the segmented time shift approach. Utilizing the same logic as the previous function, the segmented time shift function add another dimension where the indicator time series is split into N segments, finds the optimal shift level for a segment, then truncates the lagging watch data according to that last shift, and moves on to the next segment. The output is a $N \times 1$ vector of time shifts alongside a resampled stress measurement timeseries combining each shifted segment. The resulting plots show a better correspondence between peaks that are adjacent and seemingly related.

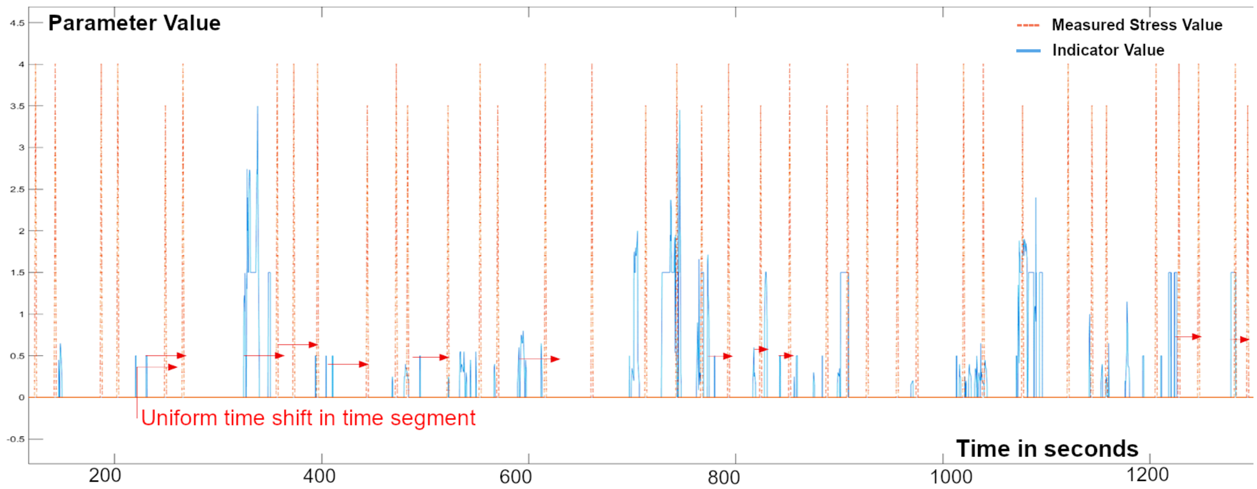


Figure 15: Applying different time shifts to stress signals.

4. Results and findings.

4.1. Model performance

4.1.1. Overall performance

To evaluate model performance, some metrics were established and calculated for each ride.

- Indicator Positive Accuracy: How often the model correctly predicts a stress peak, as a percentage of all stress peak.
- False Positive Rate: How often the model incorrectly assumes a stress peak where none has been recorded.
- Reliability: Inversely related to sensitivity. This value calculates the likelihood that a correlation between the predicted and measured time series is not incidental. This is determined by taking the larger area of the predicted and measured stress peaks, and subtracting it from the area of the entire time window of observation. This parameter can help detect if the model is showing high accuracy only because the indicator is oversensitive, and large stretches of the observation period are considered as a single detection event.

Table 3: Performance Meta-Statistics.

	POSITIVE DETECTION	FALSE POSITIVE RATE	RELIABILITY	TIME SHIFT	STRESS EVENTS/MIN
AVERAGE VALUE	50.59%	45.95%	74.53%	11.72s	1.448 events

4.1.2. Indicator assessment.

The individual indicators were evaluated according to the following characteristics:

- Accuracy: How often this indicator was present in correctly identified moments of stress.
- Time sensitivity: How narrow of a time range is this indicator active to achieve this. “High” and “Very High” denote indicator durations of a few seconds and not more. “Medium” denotes indicators that detected events that span 5 to 10 seconds. “Low” are indicators that detecting longer events than 10 seconds for a single signal satisfying the thresholds.
- Reliability and precision: How reproducible these results are with different riders and rides, using the same criteria.

Table 4: Indicator Statistics.

INDICATOR	ACCURACY	TIME-SENSITIVITY	RELIABILITY AND PRECISION
BRAKING	Very High	Very High	High.
LATERAL AVOIDANCE	High	High	Medium to High.
CADENCE SHIFT HIGH	High*	Very High.	High. *Related more to exertion than traffic conflicts. Can replace slope values.
CADENCE SHIFT LOW	High	High	High
SLOPE	Low	Low to Medium	Low.
BELL USAGE	Very High	Medium to High	High
HEAD TURNING	Medium to High	Low to Medium	Low. Clarity of video affected by lighting and rain. Rider behavior differs.
VERTICAL VIBRATIONS	Medium	Medium	Medium. Stretches of poorly surfaced road make it less time sensitive.
HANDLEBAR MOTION	Medium	Medium	Low. Phones were not always placed correctly by testers and as a result did not charge.

These findings show that most relevant indicators that can be used to predict or estimate stressful situations are already integrated in the E-bike itself, with the exception of the bell usage detection. In general, braking force, lateral avoidance, cadence reduction and bell usage are enough to detect a significant part of stress events. Additional inputs in the current configuration may increase accuracy, but at the cost of increased false positives and reduced time precision. Therefore, sensor setups II and III, as detailed in section 3.2, form the optimal package of accuracy and simplicity.

Additionally specific scenarios that were identified where stress peaks were detected, besides evident cases such as braking and weaving, were:

- Reaching the pedal-assist speed limit.
- Picking up cadence after a slope begins.
- Being in mixed traffic (cyclist/pedestrian, cyclist/car).

The first point relates more to the implementation of speed limiters in the E-Bike software, and therefore is not insightful with respect to infrastructure. The latter two points highlight the importance of not simply separating cyclists from car traffic but also providing a less stressful experience.

Stress points were more frequent during morning hours. This can be due to several reasons, among which is a traffic peak that is more pronounced than the afternoon peak, increasing interaction with cars and cyclists, in addition to poorer visibility, lighting, and colder temperatures in the morning. Notable is the fact that 4 rides occurred in foggy conditions in the morning.

From these results, it can be seen that a relation exists between these indicators and the stress measured. The reliability value suggests that the relationship is probably statistically significant. However, the false positive rate is still high. This means the indicators and thresholds need better tuning to generate more meaningful data. Positive detection is satisfactory since the number of stress events generated is quite high, suggesting that the wearables have high sensitivity to begin with, and may be overrepresenting minor events.

4.2. Identification of stress peaks and locations.

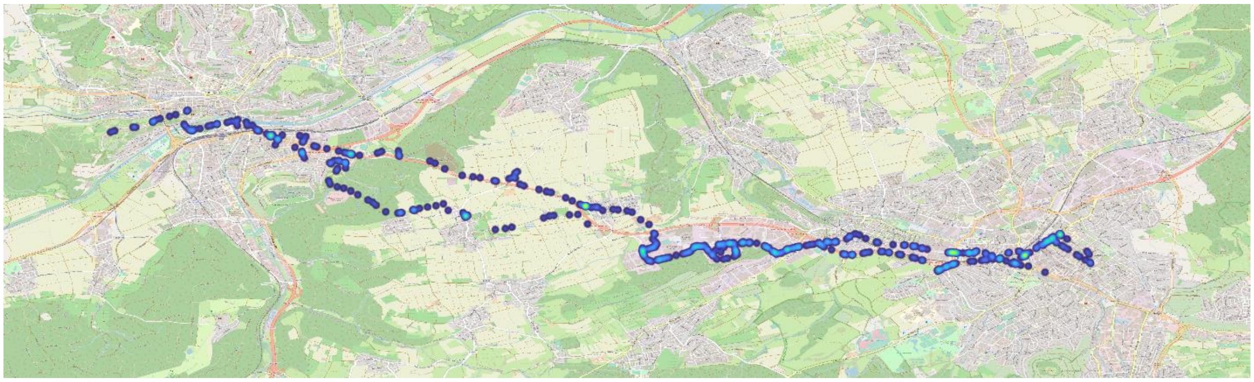


Figure 16: Heatmap of Stress Points.

The geographic distribution of stress points also confirms rider's feedback and feelings and assumptions about the route. After performing the time adjustment from cross correlation in section 3.6.2 , the stress points mapped out to more overlapping areas of stress and points that have been noticed by the riders themselves.

Common points of stress were:

- Crossing major intersections with no bike lanes.
- Turning intersections within cities, especially left turns.
- Streets with mixed traffic with cars.
- Streets with high heavy vehicle traffic.
- Cyclist and pedestrian bridges.
- Strong downhill sections with low visibility.
- Large open areas/squares with high pedestrian activity.

This is in line with the findings by Teixeira et al. (2020) that cited intersections and traffic lights, pedestrian presence, and mixed traffic as the highest stressors.

Specific areas have also been highlighted on the regular route to compare with the initial LTS assessment from section 3.1.1 (Fig. 14).

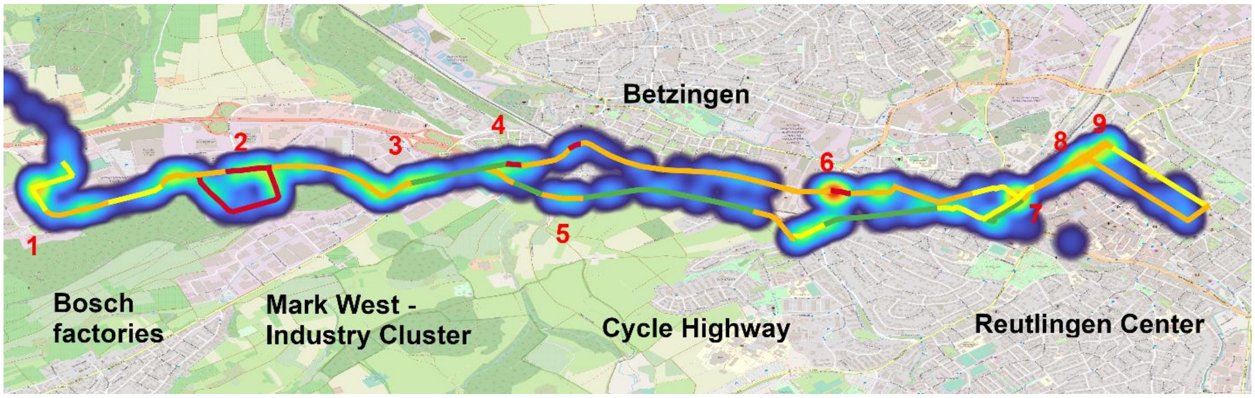


Figure 17: Moments of stress overlayed with LTS rating, with locations of interest.

The intensity of the heatmap has been adjusted to the number of rides performed through it as the section going to Tübingen was only ridden for commute rides. However, an unequal quality of data must still be assumed.

Still, the location of stress points corresponds more closely to the LTS rating than not. Among the areas of high stress intensity, points 1 through 9 are of interest.

4.2.1. Bosch Office/Factory Area.

Figure 18: Intersection near eBike Campus

This section presents more frequent conflicts than expected. This is likely due to the bidirectional advisory cycle lane, which is equal to the full width of the sidewalk it merges into. As a bus stop is present on that sidewalk, there is ambiguity on where cyclists should pass and pedestrians should stand or walk. Additionally, vehicles going to or from the right may not always expect cyclists from both directions as markings are not conspicuous.

4.2.2. Mark West industry area:

Figure 19: Mark west sidewalk lanes.

This section overall generated a high density of continuous stress points. Cyclists have no dedicated lanes and must share the sidewalk with pedestrians or the road with heavy vehicles. Participants noted their general dislike of this segment of road. From video recordings, it was noticed that some participants choose to use the sidewalk while others used the road, however this was not found to be related to their expressed experience level. The sidewalk transitions are rough and not chamfered. Additionally, temporary bus stops occupy some sidewalk space. A specific choke point was measured at 1.3 meters wide, which is already insufficient according to both FGSV and CROW guidelines, and would be even more narrow if pedestrians were present or waiting for the bus. This would then force cyclists to get on the carriageway, which is used by large trucks and has a speed limit of 50km/h.

4.2.3. Industry railway cycle track.

Figure 20: Industry track ground condition.

Although this section features a separated cyclist/pedestrian way, it also features two points of conflict that were not anticipated. Outbound, riders must move into a middle left turn lane within traffic. Due to the intermediate width of the lane and the high speed limit, drivers are often tempted to speed past cyclists which will find themselves pushed to the shoulder if not assertive enough. The transition to the left lane becomes then even more precarious. Drivers in perpendicular directions may often focus on the faster and more visible motorized traffic and in several cases did not notice cyclists intending to turn left. Inbound from Reutlingen, the cycle lane turns into a shared sidewalk. The transition is however not smooth, as the sidewalk ledge is around 7cm high. Between the train tracks, the transition into the sidewalk however is smooth, but that presents a potential to get stuck between the tracks, especially in wet conditions or in snow where the track may not be visible. Drivers waiting to merge sometimes block one of these paths or the other.

4.2.4. Betzingen pedestrian bridge and sidewalk.

Figure 21: Betzingen bridge, sidewalk and track.

The bridge was a site of some stress points, due to its narrow shape, but more significantly the exit off the bridge is a blind spot with a turn rightward. The shared sidewalk turns into a shared street or a separate path, which however due to routing was not used. To continue on the defined route, cyclists must step off the sidewalk in significant bump. At this point, right of way is not clearly defined, as vehicles moving parallel may consider the cyclist as merging traffic, and perpendicular traffic may not assign riders the same priority as drivers since they are crossing beyond the dashed line. Additionally, heavy vehicles such as buses frequently pass through this section, increasing potentially stressful interactions.

4.2.5. Cycle highway bridge and crossing.

Figure 22: Small bridge after cycling bicycle highway

This section also saw some moments of stress, as predicted, due to the strong downhill followed by a strong turn, and a barrier-narrowed bridge. Since the bridge is not clearly within line of sight at the crest of the hill, it can sometimes arrive unexpected, which coupled with its barriers, can lead to crashes with the latter or with other cyclists and pedestrians as the rider arrives with too much speed ad momentum from the downhill.

4.2.6. Bantlinstrasse intersection.

Figure 23: Bantlinstrasse left turn intersection.

This section saw two concentrations of stress. The former is at the intersection itself. This could be likely due to the long waiting time at the traffic light, which according to Zeile (2016) and CROW is a factor of discomfort. It could also be possibly due to the lack of clear markings for cyclists to cross, as traffic lights imply that cyclists should use the sidewalk, but the sidewalk too narrow to continue to serve as a shared walking/cycling space, yet there is no space at the shoulder for a cyclist to pass without getting in the way of an automobile.

Additionally, to continue forward, the cyclist must turn slightly left into a bidirectional narrow street. This maneuver is easier to perform if the cyclist is already on the carriageway. This also relates to conflicts at the crossing as a result.

4.2.7. Karlstrasse:

Figure 24: Bus and bike lanes on Karlstrasse.

This section was also cited as uncomfortable. This is most likely due to the fact that cycle lanes northbound are crossed by the buses, which leave no buffer around the lanes. Southbound, the cycle lanes exist within bus the lanes. Participants have reported that they sometimes felt anxious when a bus is behind or in front of them, due to not knowing if they should yield out of the way or to overtake a stationary bus.

4.2.8. Right turn onto Kaiserstrasse:

Figure 25: Bicycle lane transition on Kaiserstrasse.

This section transitions rather abruptly into a shared street, with the cycling lane disappearing without defining a path for the cyclist to take or a space for drivers to reserve for cyclists. This caused stress points on and after the turn. The street's width is also ambiguous; fitting easily one and a half standard automobile lanes, yet cyclists must share the space with the expectation that they are to be overtaken by other vehicles, as the wide space invites drivers to drive more quickly and aggressively.

4.2.9. Bismarkstrasse:

Figure 26: Turning left on Bismarkstrasse.

This section also saw a concentration of stress points. This can be due to waiting times, as well as navigating the turn with turning cars as in the previous turn on Kaiserstrasse. The lack of markings from one side of the cycleway to the other creates potential for conflict whenever one side is not aware of the space needed or intended to be taken by another road user.

Overall, the stress points seem to be rather representative of the traffic situation, especially when synchronized to kinematic indicators to adjust for delayed response. Theoretically, it could also be interesting to filter out stress points that do not intersect with the stress moments seen in kinematic indicators, notably those generated from long waiting times at traffic lights. However, as they were considered an aspect of comfort, they were kept in the is study, as it is not within the scope of this thesis to tune the parameters of the physiological stress sensing methodology.

From these insights, there is a visible throughline in all of the highlighted problem areas, notably the insufficient and inconsistent allocation of cyclist space. If FGSV or CROW guidelines were to be followed in full, several sections must be widened, or upgraded to separated cycle lanes, and intersections and transitions must be more clearly marked to suggest and facilitate a safe crossing where all road users are aware of one another. Crucially, heavy vehicle traffic and high speed traffic (50+km/h) must not be sharing road space with cyclists in the Mark West area. It must be sadly noted that the aforementioned area has already witnessed fatal accidents in the past and current infrastructure has not done much to mitigate this danger.

4.3. Discussion

Since the model variables and weights were selected on a theoretical basis, it is possible that other variables that were not considered can be relevant for the improvement of the model. In addition, simple filtering and combination methods were applied for indicators as the large size of the timeseries signals made simpler computations preferred. For example, Nuñez et al. (2018) has found that noise can also influence stress levels. However, due to the nonuniform availability of video footage and the associated processing requirement to evaluate it, this aspect was not considered.

In another dimension, the data from the Empatica Watches had a limited time resolution: they were sampled every second, and these values were aggregated to find peaks of stress. Therefore, they should not be taken as ground truth, but also subject to inaccuracy and inconsistency themselves. Indicators related to video were promising when conditions were right; however, they mostly faced adverse conditions due to the time span of the experiment occurring in the winter season where lighting and visibility are at their worst. Additionally, the cold temperatures affected battery performance, and this also made access to video data inconsistent. For these reasons, video data was not considered for most of the rides. Temperatures also could affect the reliability of the Empatica watches in determining stress, as riding at speed increases cold airflow and can affect skin temperature which is a metric in stress measurements.

Events that can also cause stress that are invisible kinematically are also overtaking events by drivers. For this, a sound analysis was considered, where engine sounds would be identified by a range of frequencies and amplitudes. However, this proved too complex to differentiate between a close fast overtaking and sound from a vehicle in an opposite lane that posed no danger.

There are also externalities that could affect this stress measurement. In particular, the higher occurrence of stress events in the morning hours can be a result of busier traffic conditions but also could be in part due to the riders worrying about making it in time to work or the general state of discomfort and drowsiness that can happen in the morning.

Finally, the results are limited by their sample size (15 rides) which makes trends visible but not exactly representative of the broader population. There is also a limiting factor from selection bias, where participants were for the most part experienced, all-weather cyclists. Although some inexperienced riders were scheduled to take part, they were not confident enough for the weather conditions of November/December, which frequently had rain and ice, and canceled their appointments. Additionally, the author himself took part of the data generation process, which may skew results inadvertently due to his knowledge of what is being measured. Finally, gender-dependent perceptions of stress and reactions to it, if they exist, could not be investigated in this study due to the male-dominated sample population (>90%).

5. Conclusion and outlook

5.1. Main contributions

This thesis aimed to synthesize methodology from different sectors of cycling safety research to establish a more accurate and easily deployable data collection system. Based on the comparison and analysis of kinematic and physiological data, it can be concluded that physiological and emotional stress can in many cases be also detected through kinematics. While the sample size limits the conclusiveness of the results, the process and methods explored can provide new insights in the analysis of cycling kinematics in stressful environments or conflict situations. By adding more time-sensitive indicators, the findings of this thesis can also be used to improve existing stress-sensing and mapping. With a streamlined process to collect and analyse bicycle data, based on existing sensors, it can be easily expanded in scope and used to analysis conflict and cyclist reactions in other geographical areas or in other traffic contexts and technological applications.

5.2. Future research

From what has been found, different avenues of research can be investigated in future studies. Utilizing the same methods and indicators, a model could be developed based on the more recent Empatica Embrace which includes higher polling rates. The relationship between physical exertion and stress occurrence should also be studied, as some patterns emerge among e-bike riders that are different from other cyclists, notably energy management strategies for cadence. Additionally, implicit signals of intent, such as cadence and leaning, seem to also relate to explicit signals of intent such as hand signaling, and this would be a potential area of future research. Shoulder glancing behavior is also possibly affected before and after stressors are detected, however limited quality of video data did not allow a deeper dive into this phenomenon. The before-and-after-stress reaction could then be explored. Finally, a rider’s stress response to a Human Machine Interface (HMI) safety warning would be an area of interest to assess the impact and benefit of such warnings.

6. References

Publication bibliography

ADFC-Fahrradklima-Test (2023): Ergebnisse. Available online at https://fahrradklima-test.adfc.de/ergebnisse, updated on 4/1/2023, checked on 4/1/2023.

Agrícola, Pedro M. D.; Da Silva Machado, Daniel G.; Farias Junior, Luiz F. de; do Nascimento Neto, Luiz I.; Fonteles, André I.; Da Silva, Samara K. A. et al. (2017): Slow Down and Enjoy: The Effects of Cycling Cadence on Pleasure. In *Perceptual and motor skills* 124 (1), pp. 233–247. DOI: 10.1177/0031512516672774.

Ben-Akiva, Moshe; Bierlaire, Michel (1999): Discrete Choice Methods and their Applications to Short Term Travel Decisions. In Frederick S. Hillier, Randolph W. Hall (Eds.): Handbook of Transportation Science, vol. 23. Boston, MA: Springer US (International Series in Operations Research & Management Science), pp. 5–33.

Bíl, Michal; Bílová, Martina; Müller, Ivo (2010): Critical factors in fatal collisions of adult cyclists with automobiles. In *Accident; analysis and prevention* 42 (6), pp. 1632–1636. DOI: 10.1016/j.aap.2010.04.001.

Blackledge, Jonathan M. (2013): Digital signal processing. Mathematical and computational methods, software development and applications. 2. ed. [with corr. and add.]. Oxford: WP, Woodhead Publ ([Woodhead Publishing series in electronic and optical materials], [11]).

Caviedes, Alvaro; Figliozzi, Miguel (2018): Modeling the impact of traffic conditions and bicycle facilities on cyclists’ on-road stress levels. In *Transportation Research Part F: Traffic Psychology and Behaviour* 58, pp. 488–499. DOI: 10.1016/j.trf.2018.06.032.

Dozza, Marco; Bianchi Piccinini, Giulio Francesco; Werneke, Julia (2016): Using naturalistic data to assess e-cyclist behavior. In *Transportation Research Part F: Traffic Psychology and Behaviour* 41, pp. 217–226. DOI: 10.1016/j.trf.2015.04.003.

Dozza, Marco; Werneke, Julia (2014): Introducing naturalistic cycling data: What factors influence bicyclists’ safety in the real world? In *Transportation Research Part F: Traffic Psychology and Behaviour* 24, pp. 83–91. DOI: 10.1016/j.trf.2014.04.001.

EU Directorate-General for Mobility and Transport (2021): Road safety. European Commission rewards effective initiatives and publishes 2020 figures on road fatalities. European Commission, checked on 7/29/2022.

Geller, Roger (2006): Four Types of Cyclists. Available online at https://www.portlandoregon.gov/transportation/article/264746, checked on 4/1/2023.

Giubilato, Federico; Petrone, Nicola (2012): A method for evaluating the vibrational response of racing bicycles wheels under road roughness excitation. In *Procedia Engineering* 34, pp. 409–414. DOI: 10.1016/j.proeng.2012.04.070.

Groot, Rik de (Ed.) (2016): Design manual for bicycle traffic. Ede: Crow (CROW Record, 28).

Hull, Angela; O'Holleran, Craig (2014): Bicycle infrastructure: can good design encourage cycling? In *Urban, Planning and Transport Research* 2 (1), pp. 369–406. DOI: 10.1080/21650020.2014.955210.

infas Institut für Sozialwissenschaft (2022): Mobilität in Deutschland - Wissenschaftlicher Hintergrund. Available online at http://www.mobilitaet-in-deutschland.de/, updated on 7/13/2022, checked on 8/4/2022.

Ishitake, T.; Ando, H.; Miyazaki, Y.; Matoba, F. (1998): Changes of visual performance induced by exposure to whole-body vibration. In *The Kurume medical journal* 45 (1), pp. 59–62. DOI: 10.2739/kurumemedj.45.59.

Kyriakou, Kalliopi; Resch, Bernd; Sagl, Günther; Petutschnig, Andreas; Werner, Christian; Niederseer, David et al. (2019): Detecting Moments of Stress from Measurements of Wearable Physiological Sensors. In *Sensors (Basel, Switzerland)* 19 (17). DOI: 10.3390/s19173805.

Lee, Oliver; Rasch, Alexander; Schwab, Arend L.; Dozza, Marco (2020): Modelling cyclists' comfort zones from obstacle avoidance manoeuvres. In *Accident; analysis and prevention* 144, p. 105609. DOI: 10.1016/j.aap.2020.105609.

Llorca, Carlos; Angel-Domenech, Antonio; Agustin-Gomez, Fernando; Garcia, Alfredo (2017): Motor vehicles overtaking cyclists on two-lane rural roads: Analysis on speed and lateral clearance. In *Safety Science* 92, pp. 302–310. DOI: 10.1016/j.ssci.2015.11.005.

Majumdar, Bandhan Bandhu; Mitra, Sudeshna (2019): A study on route choice preferences for commuter and non-commuter bicyclists: a case study of Kharagpur and Asansol, India. In *Transportation* 46 (5), pp. 1839–1865. DOI: 10.1007/s11116-018-9898-z.

Matthews, G.; Dorn, L.; Hoyes, T. W.; Davies, D. R.; Glendon, A. I.; Taylor, R. G. (1998): Driver stress and performance on a driving simulator. In *Human factors* 40 (1), pp. 136–149. DOI: 10.1518/001872098779480569.

Mekuria, M. C.; Furth, P. G.; Nixon, H. (2012): Low-stress bicycling and network connectivity. Available online at https://scholarworks.sjsu.edu/mti_publications/74/.

Nuñez, Javier; Teixeira, Inaian; Silva, Antônio; Zeile, Peter; Dekoninck, Luc; Botteldooren, Dick (2018): The Influence of Noise, Vibration, Cycle Paths, and Period of Day on Stress Experienced by Cyclists. In *Sustainability* 10 (7), p. 2379. DOI: 10.3390/su10072379.

Pucher, John; Buehler, Ralph (2017): Cycling towards a more sustainable transport future. In *Transport Reviews* 37 (6), pp. 689–694. DOI: 10.1080/01441647.2017.1340234.

Rayaprolu, Hema S.; Llorca, Carlos; Moeckel, Rolf (2020): Impact of bicycle highways on commuter mode choice: A scenario analysis. In *Environment and Planning B: Urban Analytics and City Science* 47 (4), pp. 662–677. DOI: 10.1177/2399808318797334.

Ritter, Frank E.; Reifers, Andrew L.; Klein, Laura Cousino; Schoelles, Michael J. (2007): Lessons from Defining Theories of Stress for Cognitive Architectures. In Wayne D. edt Gray (Ed.): Integrated models of cognition systems. New York, Oxford: Oxford University Press (Series on cognitive models and architectures), pp. 254–262.

Rowden, Peter; Matthews, Gerald; Watson, Barry; Biggs, Herbert (2011): The relative impact of work-related stress, life stress and driving environment stress on driving outcomes. In *Accident; analysis and prevention* 43 (4), pp. 1332–1340. DOI: 10.1016/j.aap.2011.02.004.

Sano, Akane; Taylor, Sara; McHill, Andrew W.; Phillips, Andrew Jk; Barger, Laura K.; Klerman, Elizabeth; Picard, Rosalind (2018): Identifying Objective Physiological Markers and Modifiable Behaviors for Self-Reported Stress and Mental Health Status Using Wearable Sensors and Mobile Phones: Observational Study. In *Journal of medical Internet research* 20 (6), e210. DOI: 10.2196/jmir.9410.

Schepers, Paul; Agerholm, Niels; Amoros, Emmanuelle; Benington, Rob; Bjørnskau, Torkel; Dhondt, Stijn et al. (2015): An international review of the frequency of single-bicycle crashes (SBCs) and their relation to bicycle modal share. In *Injury prevention : journal of the International Society for Child and Adolescent Injury Prevention* 21 (e1), e138-43. DOI: 10.1136/injuryprev-2013-040964.

Teixeira, Inaian Pignatti; Da Rodrigues Silva, Antônio Nélson; Schwanen, Tim; Manzato, Gustavo Garcia; Dörrzapf, Linda; Zeile, Peter et al. (2020): Does cycling infrastructure reduce stress biomarkers in commuting cyclists? A comparison of five European cities. In *Journal of Transport Geography* 88, p. 102830. DOI: 10.1016/j.jtrangeo.2020.102830.

Trimpop, Rüdiger M. (1996): Risk homeostasis theory: Problems of the past and promises for the future. In *Safety Science* 22 (1-3), pp. 119–130. DOI: 10.1016/0925-7535(96)00010-0.

Vos, Jonas de; Schwanen, Tim; van Acker, Veronique; Witlox, Frank (2019): Do satisfying walking and cycling trips result in more future trips with active travel modes? An exploratory study. In *International Journal of Sustainable Transportation* 13 (3), pp. 180–196. DOI: 10.1080/15568318.2018.1456580.

Zeile, Peter; Resch, Bernd; Loidl, Martin; Petutschnig, Andreas; Dörrzapf, Linda (2016): Urban Emotions and Cycling Experience – enriching traffic planning for cyclists with human sensor data. In *giforum* 4 (1), pp. 204–216. DOI: 10.1553/giscience2016_01_s204.

Appendix:

Appendix A: Questionnaire.

Naturalistic Experiment for Cycling Stress Data.

Dear colleagues,

We are conducting an experiment for measuring cyclist stress across different locations and in different traffic situations.

We are recruiting volunteer cyclists internally who would be able to cycle using our instrumented bicycles along one route. A section of the route will be predefined to make it common and comparable among different riders. The ride will consist of a ~1h round-trip from the campus during the workday.

If you want to perform a ride during your morning or evening commute, we also propose the routes starting near Tubingen and Reutlingen Hbf., respectively; and ending at the Bosch E-Bike Campus.

If you are interested, please proceed to fill out the survey form on the following pages. More details on the experiment are provided below.

Experiment Description:

The objective of this research is to study the relation between the handling of the bicycle and the cyclist’s experience of and level of stress.

For this section, we will describe the experimental conditions under which you will ride the instrumented bicycle and collect data.

We will be collecting the following data during the duration of the ride on the pre-defined section. If you are performing a commute trip, this will not be collected or processed during your ride from home to the start point of the predefined route.

1. Health Data (used to measure stress level):
    a. Heart rate.
    b. Skin temperature.
    c. Skin conductance.
2. Ride Data (used to detect changes in state and events):
    a. Hand placement on the handlebars.
    b. Face orientation/turning during the ride (Video).
    c. Short range view of the road ahead (Video).
    d. GPS data – Speed, location, acceleration etc. Location data is only used to synchronize events to specific sections of the route. We will not have GPS data before the collection is activated at the beginning of the route.

As you ride, you will be asked to ride on the route as you would normally after having activated the on-board computer at the beginning of the route. From there, you will be asked to follow a defined route to/from the E-Bike Campus. If any conflicts occur on the way, you are asked –if you can remember – to report this after the ride in the survey. We will hand you the survey after your ride(s).

This survey will also ask you about your overall level of comfort and stress throughout the ride and to locate approximately where conflicts occurred. This will allow us to find conflicts later in the data if they were not detected at the time of occurrence.

For the purpose of validating data, we will associate a rider ID with your personal information temporarily in case we need to review details about a ride with you. Once the information has been validated and the data collection is complete, this identifier key will be removed. Video used for analysis will also be anonymized after the face angle is measured.

Do you understand and consent to the collection of data as described above?

☐Yes, I consent to the above terms of data collection and am willing to participate.

☐No, I reject the data collection, and would not participate in this study as a rider.

If you answered “No”, we would kindly ask you not to send out your response, to reduce the number of documents to be processed.

Name: ___________ Department: EB/_____________

Internal Email Address: _______________

If you would like to participate, please fill the following pages as well.

Your profile:

1. Are you present on the Bosch E-Bike Campus twice a week at least?

☐Yes ☐No ☐No, but willing to go more often

2. In/Near which city do you live?

☐Reutlingen ☐Tübingen ☐Other (i.e. Wannweil, Mössingen, Engstingen…): ____________

3. How regularly do you cycle?

☐As a main mode of commuting/Several times a week

☐Once to a couple times a week

☐Once to a couple times a month

☐Never

4. Do you consider yourself a:
   ☐ Beginner… ☐Intermediate… ☐Experienced… cyclist?
5. Do you cycle depending on the weather or year-long?
   ☐Only on sunny days.
   ☐On sunny and/or rainy days. ☐In all weather (including rain and snow).

6. What day(s) are you present in person at the Campus?
   ☐Monday ☐Tuesday ☐Wednesday ☐Thursday ☐Friday ☐Irregularly

7. On which of the following days would you be available to ride? (Select up to 3)
   Monday: ☐ 21.11 ☐28.11 ☐5.12 ☐12.12
   Tuesday: ☐ 22.11 ☐29.11 ☐6.12 ☐13.12
   Wednesday: ☐ 23.11 ☐30.11 ☐7.12 ☐14.12

Thursday: ☐ 24.11 ☐01.12 ☐8.12 ☐15.12

Friday: ☐ 25.11 ☐02.12 ☐9.12 ☐16.12

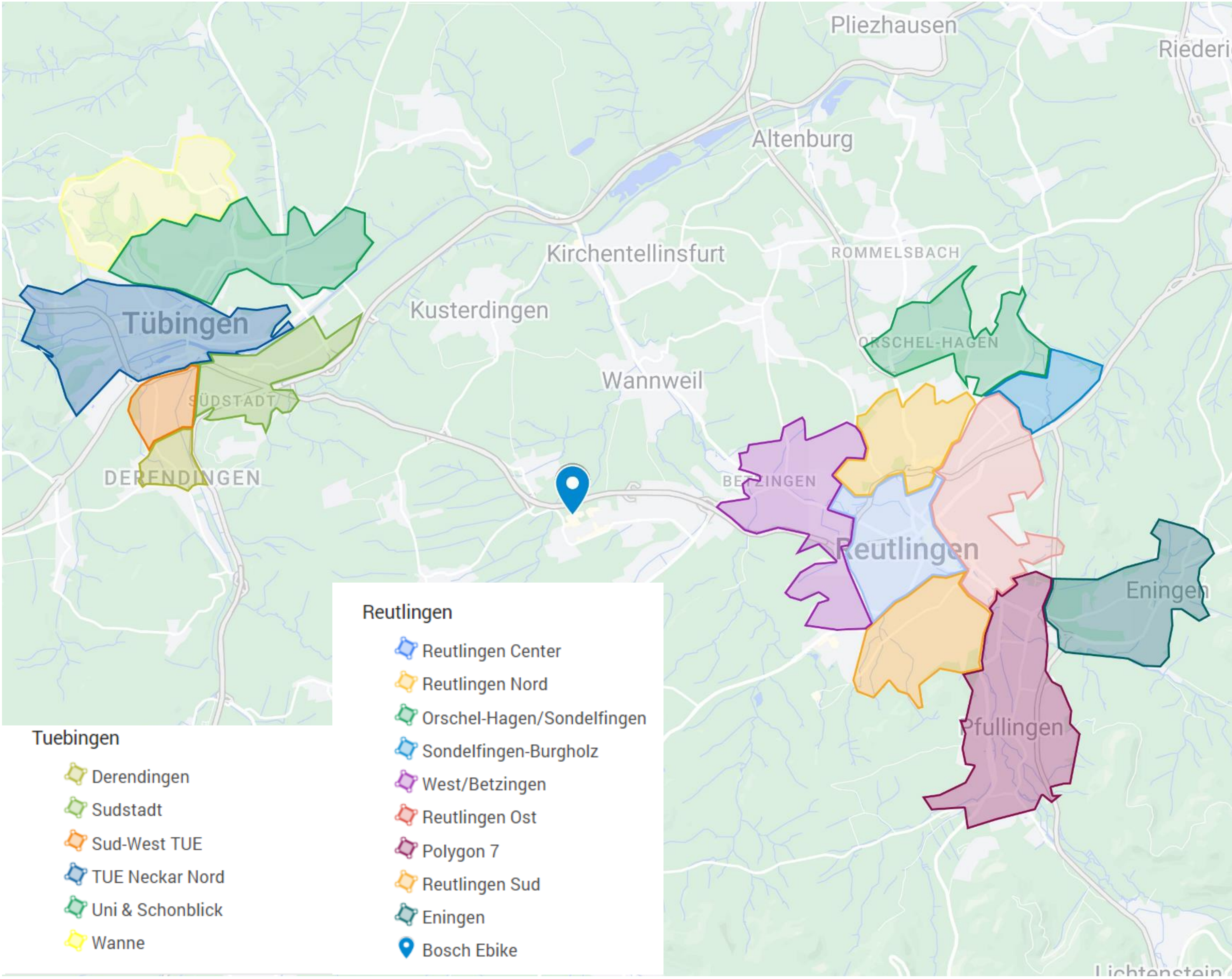
At which times would you be able to ride? Mark with a checkmark according to your date preferences, chronologically.

Selected Day	10:30-11:30	13:15-14:15	15:00-16:00	Commute (EOD commute from EB followed by morning commute to EB the next day. See next page for map)
Day 1				
Day 2				
Day 3				

Thank you for your time and for your interest! Please send your response to

fixed-term.Alameddine.Zouheir@de.bosch.com with the subject “Participation Form”.

Routes: If you commute by bicycle, from which zone do you begin your route to work? <u>Please highlight the zone with dashed lines</u>. From this zone, please also <u>trace an approximate path</u> to the Bosch E-Bike Campus. This will be used to make a common starting point and route that minimizes detours for all participants**.**



Appendix B: Extra figures:

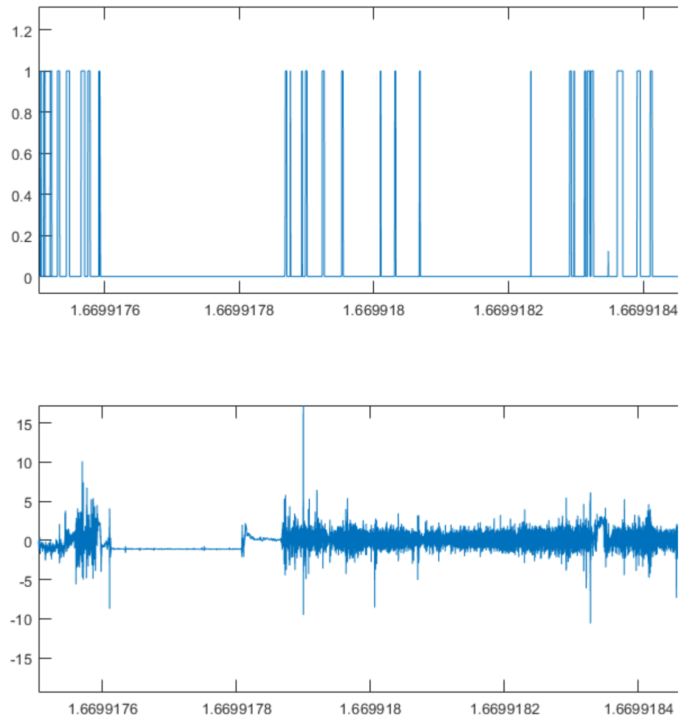


Figure B.1: Avoidance Maneuver signal.

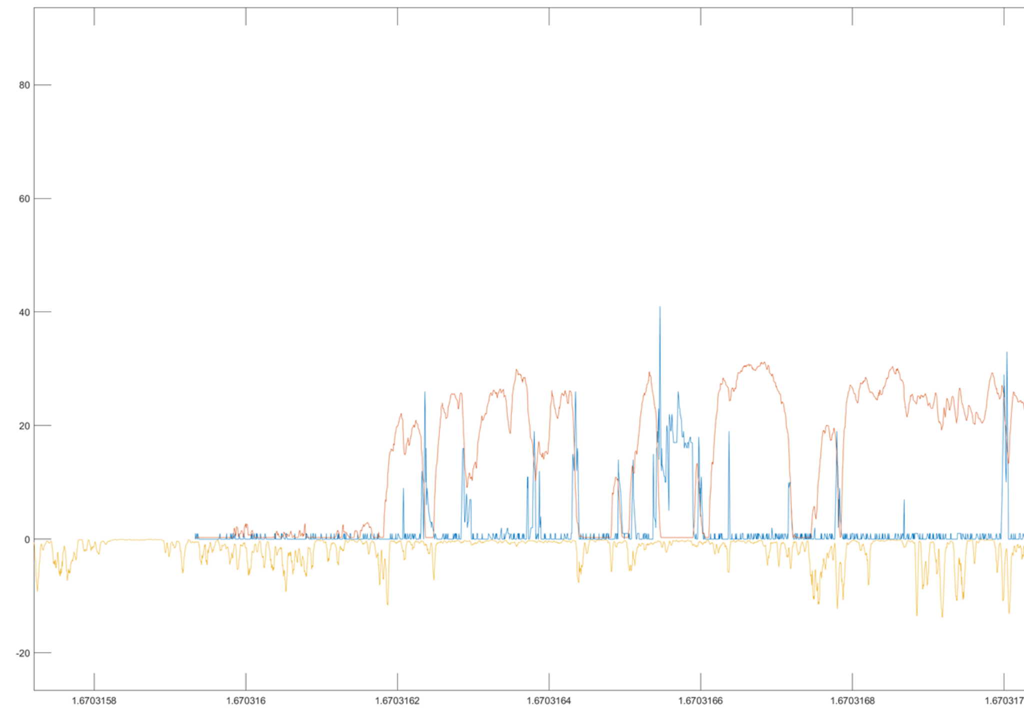


Figure B.2: Adjusted GSR signal versus speed and braking data.

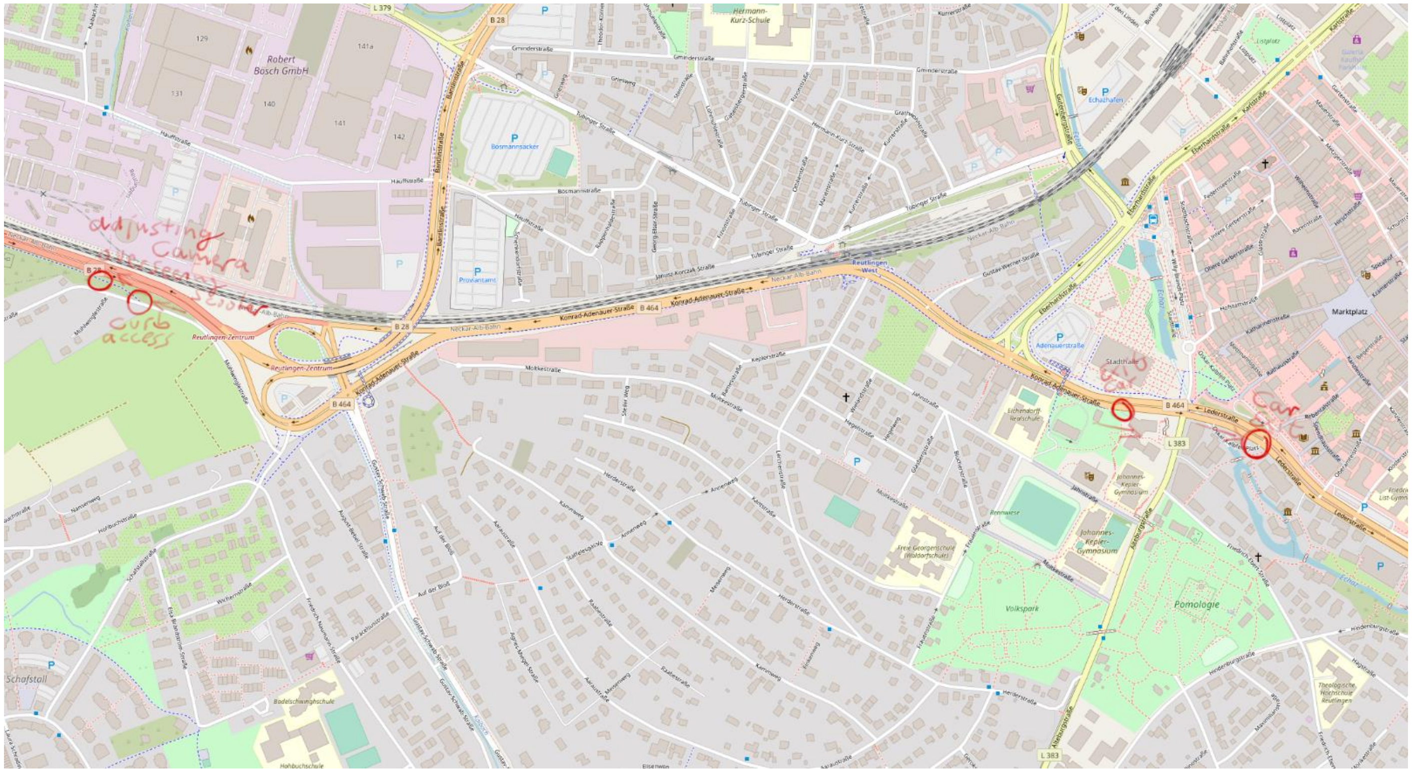


Figure B 3: Map of the route with rider feedback on experienced stress and conflict points.

Figure B.7: Poster to advertise the test rides and find participants.