Assessing Cyclists’ Cognitive Load: The Influence of Urban Cycling Infrastructure Designs and Traffic Volumes

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Abstract

Urban planning strategies have a fundamental impact on people's choice of transport. Many European cities are working to shift towards facilitating more sustainable modes of transport and reducing motorised traffic.

Cognitive load can be considered the mental resources that are required to perform a variety of tasks, such as cycling in various traffic situations. Human factors, i.e., cognitive load, affect people's perceived safety and their choice of transport mode. There is a lack of naturalistic cycling data focusing on the influence of different traffic conditions on cognitive load.

Therefore, this study aims to investigate the influence of different traffic situations on the cognitive load of cyclists. For that, people participate in a naturalistic study, cycling through the Austrian city of Vienna, in order to advance research regarding the effects of various built environment conditions and traffic volume on cognitive load. The effects of the different conditions are compared. Cognitive load can be assessed by physiological measurements (i.e., through Empatica E4 smartwatch) in the form of electrodermal activity (EDA). For this study, EDA has been normalised compared to people's baseline physiological responses.

A panel regression model is used to investigate the effect of different built environment conditions and traffic volume on cyclists' cognitive load. The results confirm differences between the various traffic segments on cognitive load but are not in line with the hypothesis that higher traffic volume leads to increased cognitive load. Although not all results confirm the hypotheses, this study shows that cognitive load, measured through EDA can improve understanding of the effect of different built environment conditions on cyclists' cognitive load in a dynamic traffic context.

Keywords: Cycling, Cognitive Load, Built Environment, Infrastructure Design, Traffic Volume, Panel Regression Model

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1. Introduction

1.1 Problem Background

Greenhouse gas (GHG) emissions are the largest contributor to global warming (IPCC, 2014). Human activities, particularly the utilisation of fossil fuels for transportation, electricity, and heat, all lead to high GHG emissions (Perera, 2018). After industry, the transportation sector was responsible for the highest global GHG emissions in 2021 (European Commission, 2023). Among the different modes of transport, car traffic is the largest source of GHG emissions in the EU (Kazancoglu et al., 2021). The GHG emissions for global transport have been growing steadily at 2% per year since 1990, with North America, Europe, and East Asia being the largest contributors (Lamb et al., 2021). A significant potential for mitigating these emissions lies in shifting from carbon-intensive to low-carbon transportation methods for travelling, which rely on large-scale policy changes on international, national, and local levels (Cuenot et al., 2012).

Around the world, and particularly in Europe, cities are therefore developing more environmentally friendly plans to move away from car-centric transportation networks (Nieuwenhuijsen & Khreis, 2016). Active transport combined with a reduction in private motorised traffic has been shown to have a positive impact on public health (De Nazelle et al., 2011). Cycling provides benefits to physical activity and has been shown to be positively associated with cardiovascular health and cognitive function while being negatively associated with cancer mortality and morbidity (Oja et al., 2011, Nieuwenhuijsen, 2016). A recent cost-benefit analysis including climate, pollution, and health has shown that the cost of automobility amounts to €500 billion annually (including costs of climate change impacts, pollution, accidents, infrastructure, vehicle, and energy production). In comparison, cycling is associated with benefits of €34 billion (Gössling et al., 2019a).

Urban planning that shifts from car infrastructure towards more sustainable infrastructure can be a strategic approach to transition from an environment that is more detrimental to health to one that is more beneficial (Nieuwenhuijsen, 2020). The discrepancy in impacts between active transport and motorised traffic highlights the significance of cycling as a means of improving public health, reducing environmental impact, and generating economic benefits, underlying the importance of conducting further analysis to ascertain the societal and individual effects of cycling.

In their recent study, Habib et al. (2024) examined how human factors affect cycling, through perception, cognitive load, and behaviour and argued that these factors affect people's perceived safety in the traffic context. Perceived safety, in turn, affects the likelihood of people choosing sustainable alternatives (i.e., cycling) to motorised vehicles in urban settings (Gössling et al., 2019b). Previous research has focused on different traffic conditions on cyclists' cognitive load in virtual reality (VR) laboratory studies (e.g., Guo et al., 2023), or studied the influence of traffic on car drivers' cognitive load (e.g., Nilsson et al., 2022). The benefit of VR and simulator studies is the control of variables, e.g., weather, traffic volume, and interactions with other traffic participants (O'Hern et al., 2017). A drawback of those VR laboratory studies is, that they cannot replicate real-world conditions as in naturalistic studies (Rupi & Krizek, 2019). Johnson et al. (2010) argued that naturalistic studies are the best approach to understanding cycling behaviour as they provide real-world information on traffic interactions between different traffic participants.

With this study, we focus on the varying effects of the built environment conditions, defined by different road infrastructure designs on cyclists. In particular, conducting a naturalistic study allows to quantify the differences that several built environment conditions have on the cognitive load experienced by cyclists in Vienna. With that, we can answer how different traffic segments defined by built environment conditions differ in their influence on the cognitive load of cyclists. Therefore, the objective of this study is to contribute to the knowledge of the influence of different traffic designs and volumes on cyclists' cognitive load in the context of urban traffic in Vienna, Austria.

1.2 Influence of Built Environment Conditions on Cyclists in the Urban Context

The built environment can influence people's willingness to cycle in urban contexts through a variety of factors (Ye & Titheridge, 2017, Gössling et al., 2019a). People's willingness to cycle is negatively affected when traffic is perceived as dangerous, distances are long, and exposure to noise and particle pollution (e.g., coming from motor vehicle exhaust) is high (Gössling et al., 2019b, Atkinson et al., 2018). Chuang et al. (2013) showed in their study that the distance between bicycles and cars in traffic affects cyclists' behaviours (e.g., more stable riding with less movement, choosing to maintain constant speed). Harvey et al. (2008) surveyed cyclists and found that people will choose longer rather than shorter travel routes if they can thereby increase their safety and comfort. Research has shown that people are more likely to use bicycles for travel when cycling lanes are physically separated from car traffic, travel distances are short, and perceptions of safety for cyclists are high (Gössling et al., 2019a).

In the context of traffic, the objective safety of cyclists reflects more quantitative aspects of safety (i.e., the number of accidents involving cyclists and the risks of accidents) while perceived safety refers to cyclists' assessment of traffic situations, e.g., how safe a crossing is perceived (Matviienko et al., 2021). Since perceived safety directly influences people's decision to use bicycles as a means of transport (Heinen et al., 2011), it is crucial to focus on this aspect when considering the different traffic conditions for cyclists in urban traffic. Choosing the bicycle as the mode of transportation is driven rather by perceived safety than by the objective and quantifiable aspects of road safety (Dill & Voros, 2007).

Furthermore, distances for people living in inner cities have a significant impact on people's travel mode choice, i.e., on whether these residents cycle, walk, or choose motorised transport such as cars or public transport (Scheiner, 2010, Stefansdottir et al., 2019). A study by Sallis et al. (2016) showed that neighbourhoods that are planned in a way that accommodates the needs of pedestrians significantly increase the level of walking. The built environment can therefore exert a direct impact on people's travel choices and satisfaction, e.g., by factors related to the immediate area around the home and workplace (Ye & Titheridge, 2017).

To facilitate more cycling and create cycling cultures within cities, urban planning needs to take into account cyclists' concerns about safety, comfort and interrelation with car traffic (Aldred, 2013). Consequently, urban planning strategies must be adopted by cities that wish to encourage a greater number of individuals to utilise the bicycle as a mode of transport (Buehler et al., 2017b). A cycling-friendly environment facilitates the ease of travelling and thus increases travel satisfaction (Ye & Titheridge, 2017).

For cycling in urban contexts, the interaction with the environment and parts of the infrastructure can exert its influence on cyclists' cognitive load which further affects their perceived safety in various traffic situations and consequently, people's choice to choose the bicycle as a mode of transportation (Habib et al., 2024, Heinen et al., 2011).

1.3 The Current Study

To this date, there has been little research on the influence of urban traffic on cyclists' cognitive load. Cognitive load affects people's perceived safety, which in turn affects their likelihood of choosing the bicycle as a mode of transport in urban traffic (Gössling et al., 2019b, Habib et al., 2024). Nevertheless, as the majority of research focuses on the impact of mental load on cycling or motorised driving behaviour (Habib et al., 2024), it is of significant importance to also examine how different traffic conditions affect cyclists' cognitive load. To ascertain the influence of differing built environment conditions, physiological measures of cognitive load will be employed to be able to quantify and distinguish those differences based on various traffic conditions.

As there are few naturalistic studies quantifying these differences, this study aims to advance research in the field by investigating how the impact of the built environment on cyclists' is reflected in different cognitive loads, following a deductive approach, by understanding the role of human factors (i.e., cognitive load) in designing better road infrastructure for cycling in Vienna. Results will be important to increase knowledge regarding factors that are important in understanding cyclists' perceived safety and cognitive load, and through accommodating their needs, increase the modal share of cyclists. Quantifying cognitive load will be done by collecting and analysing data from physiological data readings and self-report measures of people cycling along a pre-determined route through the city with different built environment conditions. Specifically, differences in different types of road facilities for cyclists in the city will be considered. These include mixed paths shared with pedestrians, designated cycle paths, roads shared with cars, and roads shared with cars with a continuous line separating the cycle lane from motorised traffic. Based on the background and information presented, the following research questions will be addressed.

1.3.1 Research Questions

1. What are the differences in the cognitive load experienced by cyclists based on different road-geometric infrastructure designs
    a. mixed cycling path (shared with pedestrians),
    b. designated cycling path (separated from pedestrians with a line),
    c. mixed cycling traffic on roads with cars (no line),
    d. mixed cycling traffic on roads with cars (separated by a continuous line),

    of people who cycle in Vienna, Austria?

2. What are the differences in cyclists' cognitive load experience based on high and low traffic volume (i.e., peak vs off-peak traffic) of people cycling in Vienna, Austria?

1.3.2 Hypothesis

As previous studies have shown, people who choose cycling as a mode of transport are willing to cover longer distances if they can thereby increase their safety and comfort (e.g., Harvey et al., 2008). Furthermore, cyclists who have to share the road with cars experience feelings of threat and emotional stress (Chataway et al., 2014, Heesch et al., 2011). Therefore, I hypothesise that the built environment influences cyclists' cognitive load in the following ways:

1. Traffic density and shared roads with cars (with no separation) lead to higher cognitive load than shared roads with cars (separated by line), than designated cycling lanes (shared with pedestrians), than designated cycling lanes (separated from pedestrians with line) for cyclists in Vienna, Austria.

$H_0 = \mu_{mixed} - \mu_{not\text{-}mixed} = 0$ *and* $H_a = \mu_{mixed} - \mu_{not\text{-}mixed} > 0$

Previous research has shown that higher traffic volumes have a negative effect on levels of leisure cycling (Foster et al., 2011). I therefore hypothesise that:

2. The peak traffic condition (high traffic volume) elicits a higher cognitive load than the off-peak condition (low traffic volume) for cyclists in Vienna, Austria.

$H_0 = \mu_{peak} - \mu_{off\text{-}peak} = 0$ *and* $H_a = \mu_{peak} - \mu_{off\text{-}peak} > 0$

Thus, the density of traffic and shared roads with other road users will increase cognitive load which may discourage people from using bicycles as a mode of transport. The more the cycling infrastructure is separated from car traffic through the built environment, the lower the cognitive load for cyclists.

1.4 Thesis structure

Chapter 1.2 provides a summary of research on the relationship between the built environment in urban contexts and cyclists' behaviour, perceptions of safety, and cognitive load. The section 1.3 describes the current study and introduces the research questions and hypotheses. Chapter 2 discusses the concept of cognitive load in research and the different ways it has been measured by utilising subjective and physiological measurements. In the Methodology section (3), information regarding the data collection will be presented (i.e., location and experimental route, recruitment, instruments, and procedure), as well as data processing and data analytic methods. In the Results section (4), descriptive statistics are presented before the results of the regression model are presented. The Discussion section (5) will compare this study with previous research, focus on the limitations of this study, and provide possible directions for future research.

2. Literature Review

2.1 Cognitive Load

This second chapter summarises previous research on cognitive load and how it is usually conceptualised and measured using subjective and physiological methods.

Cognitive load is considered multidimensional, defined by the mental cost of subsequent cognitive tasks (Paas et al., 1994), and further as a reserve of mental resources that are required to perform a variety of tasks (Armougum et al., 2019). It can be represented as a dynamic variable that changes and is influenced by the interrelationship between task demands and cognitive processes (Babiloni, 2019). The task-oriented mental processes that constitute cognitive load are not observable through behavioural methods (Kalyuga, 2011). Cognitive load interacts with causal factors (which influence cognitive load) and assessment factors (which are influenced by cognitive load) (ibid.). Causal factors are the various characteristics of the tasks, the environment, characteristics of the learner, interactions between learner and environment, and the task (see figure 1). Assessment factors are mental load, mental effort, and mental performance (ibid.).

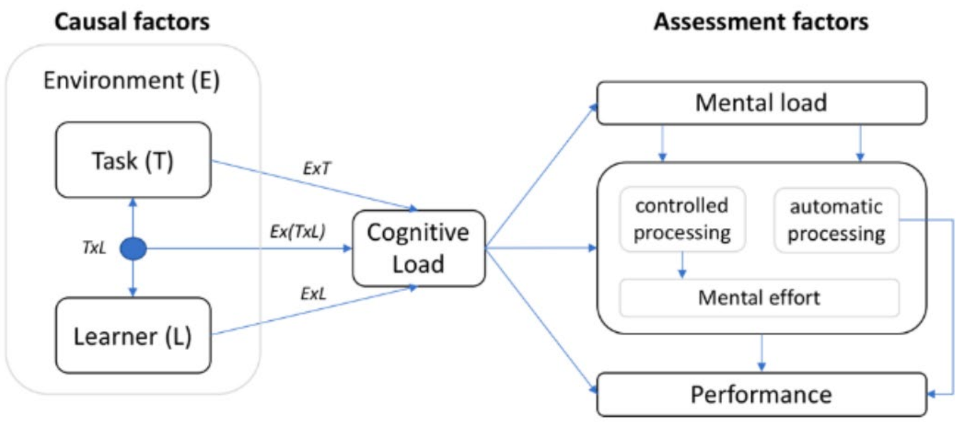

Figure 1. Causal factors and assessment factors (Source: Orru & Longo (2019), p.4).

Understanding the concept is the first step and provides the basis for empirical analysis and practical application. The following section focuses on different methods to measure cognitive load. After understanding how it is measured, the next step is to discuss the practical implementation in the form of a naturalistic study.

2.1.1 Cognitive Load Measurement

Traditionally, cognitive load has been assessed using self-report measures in educational research (Vanneste et al., 2021). Self-report measures using multidimensional scales can measure cognitive load more accurately than those utilising unidimensional scales (ibid.). In the human factors and ergonomics field, a frequently used multidimensional scale is the NASA Task Load Index (Hart & Staveland, 1988). There, the workload is assessed with five scales where cognitive load is closely linked to the mental demand assessment factor (Vanneste et al., 2021).

In addition to self-report measures, many studies looked into physiological measurements to indicate cognitive load (Agarwal et al., 2021). Cognitive load and physiological activity can be correlated with each other because cognitive demands can lead to automatic and unconscious responses of the autonomic nervous system (Wiberg et al., 2015).

More recently, these physiological measures have been applied in traffic research, as the advantage of using physiological measures for cognitive load over self-report measures is that they allow continuous recording of cognitive load and do not interfere with the driving task (Nilsson et al., 2022). Most of the studies that investigate physiological measurements of cognitive load in traffic focus on car driver's cognitive load (Nilsson et al., 2022, Lohani et al., 2019, Wiberg et al., 2015). Further research is needed to focus on measures of cognitive load in cyclists to gain insights into the influence of the built environment and changing infrastructure for people cycling in urban traffic (Habib et al., 2024).

The human cognitive system is always processing information, determining whether the information can be related to previous knowledge and is responsible for responding to the situational aspects of the environment (Buchwald et al., 2019). Studies that have used a variety of physiological measures to analyse their data have been able to predict cognitive load with higher accuracy and in a more comprehensive way (Agarwal et al., 2021, Zhang et al., 2014).

Electrodermal Activity

Previous research has shown that different states of cognitive load can be reflected in electrodermal activity (EDA; also known as galvanic skin response), with increasing cognitive load being associated with increased EDA levels (Ayres et al., 2021, Lohani et al., 2019). Through a sensor that is attached to the skin (often on the hand or wrist), the skin's electrical conductance can be determined (Nourbakhsh et al., 2012). Variations in skin moisture (i.e., sweat level) are associated with changes in skin conductance and can provide information about the sympathetic nervous system (ibid). The components of skin conductance level (SCL) and skin conductance response (SCR) can be identified for the EDA signal. The former measures psychophysiological activity and is characterised by slow changes for a given time. The latter can reflect more sudden changes, which can be distinguished by peaks of the EDA signals (Ayres et al., 2021, Braithwaite et al., 2013). A study by Mehler et al. (2012) has shown that at different levels of induced cognitive load, the function of EDA is related to increasing cognitive load, thus validating the sensitivity of measuring EDA. More recently, Vanneste et al. (2021) have argued that EDA measures reflect only a proportion of the cognitive load's variance, and further, that a combination of various physiological measures ought to increase the accuracy of cognitive load measurement and the proportion of explained variance, i.e., by combining EDA measures with eye tracking (Marquart et al., 2015) and heart rate measures (Solhjoo et al., 2019).

Heart Rate and Heart Rate Variability

Heart rate measures are a common method for determining cognitive load because cardiovascular activity is associated with physical and mental demands (Hettiarachchi et al., 2018, Fredericks et al., 2005). While heart rate (HR) is influenced by factors of both physiological and mental nature, the difficulty lies in differentiating those factors. Through a thoroughly conducted study, Mehler et al. (2012) provided evidence that HR can serve as an accurate measure of cognitive load variations, with increasing cognitive workload being associated with increases in HR. Commonly, HR is measured through electrocardiography (ECG) recording devices, with HR being the number of heartbeats in a given minute (Lohani et al., 2019). More recently, it can be measured through wearable devices (e.g., Polar H10 chest belt) (ibid.). Devices such as the Polar H10 chest belt have shown very high accuracy for ECG measures (Terbizan et al., 2002).

Another ECG measure is heart rate variability (HRV). While HR can be constant, the variation of time between two heartbeats may vary and is called HRV (Achten & Jeukendrup, 2003). Whilst HR increases with increasing mental workload, HRV decreases (Lohani et al., 2019). Cognitive load also affects blood pressure, which subsequently results in a decreased HRV, and thus has an indirect effect (Ayres et al., 2021). Generally, HR is superior to HRV in measuring cognitive load as the changes can be detected faster than HRV (ibid.).

Eye-tracking

Eye-tracking devices have also been used to determine cognitive load (Marquart et al., 2015). Previous research has shown a strong relationship between pupil dilation and cognitive task demands (Kahneman & Beatty, 1966, Van Orden et al., 2001), as pupil activity provides information about the autonomic nervous system and subsequently cognitive activity (Eckstein et al., 2017). The pupil activity can provide information as increasing pupil diameters are associated with increased cognitive load (Lohani et al., 2019). An advantage of eye-tracking devices is that they also provide information on conscious processes (e.g., focus of the eyes) in addition to autonomic processes (e.g., blink rate and pupil dilation) (Ayres et al., 2021). The additional information regarding conscious processes then provides a more detailed picture of cognitive load. Furthermore, the blink rate is related to the cognitive workload of a given task (Tsai et al., 2007). Fixation of the eyes, compared to the previous two measures reflects more conscious behaviour (Ayres et al., 2021). To assess the cognitive load, fixation rate, fixation duration, and transition rate are used as the most common measures, where shorter fixation duration and more frequent fixation rate are associated with higher cognitive load in active tasks like cycling in traffic (ibid.).

In general, cognitive load that is induced by a specific task cannot be considered completely in isolation (Nilsson et al., 2022). Situation- and person-specific factors may influence cognitive load through several mechanisms. Situation-specific factors may show their influences through the complexity of traffic demands (Di Flumeri et al., 2018, Nilsson et al., 2022). In contrast, human-specific factors may show their influences through the current mental state and level of fatigue (Schoofs et al., 2008, Tanaka et al., 2009). Fatigue is a factor that places a demand on cognition that is not considered an aspect of cognitive load (Nilsson et al., 2022). Therefore, a pre-questionnaire assesses human-specific factors, such as the amount of sleep, and consumption of caffeine, alcohol, and nicotine.

Utilising cognitive load and its measurements in this study context

Having explored cognitive load and its measurement, it is clear that applying the concept can provide insight into how external factors, such as traffic conditions can affect cyclists' perceptions of traffic. Understanding how cognitive load is conceptualised and measured, through self-reports and physiological measures that can quantify the difference in cognitive load, is particularly relevant to comprehending the varying cognitive demands of road conditions and traffic interactions on cyclists.

Building on this concept, the methodology section outlines the context in which this study takes place, the route and the instruments used to capture the differences between the route segments. By applying statistical analysis based on the methodology, cognitive load is assessed in different traffic conditions thereby providing empirical data to test the hypotheses.

3. Methodology

The methodology chapter addresses the research process of the thesis, and more specifically how the data collection (3.1) for the naturalistic investigation was carried out. The context in which took place as well as the procedure of the experiment will be discussed. Furthermore, a detailed overview of the data processing (3.2) activities will be given to show how the data were prepared for the analysis (3.3).

In order to answer the research questions of this study, a naturalistic study was designed in which participants cycled twice along a predetermined route of 4.98 km in Vienna, Austria for approximately 20 minutes each time. Dividing the route into different sections and cycling at two times allowed to gather information on the impact of different traffic segments and traffic volume. For that, the participants cycled with an instrumented bicycle. The bicycle is equipped with sensors to collect information about speed, acceleration, steering and braking behaviour. Participants were also equipped with a range of devices to measure physiological responses while cycling, which provides information about the cognitive load experienced during the task. The data analysis requires the application of several research methods, including precedent large-scale data collection and management, and multivariate analysis in the form of panel regression.

3.1 Data Collection

3.1.1 Location

The naturalistic study was conducted in Vienna, Austria. The city has a population of around two million inhabitants. Although the city has an excellent public transport network (Buehler et al., 2017a), it is still largely focused on car infrastructure. In recent years, more attention has been paid to cycling in infrastructure planning. Nevertheless, in many cases, cyclists have to share the road with motorised vehicles.

Traditionally, cycling is not considered a defining part of Vienna’s transport culture, with public transport and motorised traffic constituting a larger role in most people's choice of transport (Rauhofer, 2019). In comparison to some other European cities of comparable size, Vienna has a lower modal share of cycling, around 9% in 2022. This can be attributed to the hilly topography and the fact that cycling is not a central mode of transport in the city's culture (Buehler et al., 2017b, Wien, 2023). The latter is also reflected in studies about people's perspectives on bicycles as a mode of transport in Vienna (Füssl & Haupt, 2017). The studies indicate that the respondents perceive cycling as not normal but rather extraordinary. Additionally, they express concern about the potential risks associated with exposure to high-traffic areas in urban cycling (Füssl & Haupt, 2017, Mobilitätsagentur, 2016).

Other cities with a higher modal share of cyclists have commonly adapted to the needs of cyclists by having a higher share of physically separated bike lanes in comparison to roads that are shared with cars (e.g., in Rotterdam and Copenhagen), while around two-thirds of the roads in Vienna are used by motorised transportation users (Furchtlehner & Lička, 2019, Buehler et al., 2017b).

3.1.2 Experiment Route

The route was chosen to include distinct types of traffic infrastructure designs and had the same start and end point B (see figure 2).

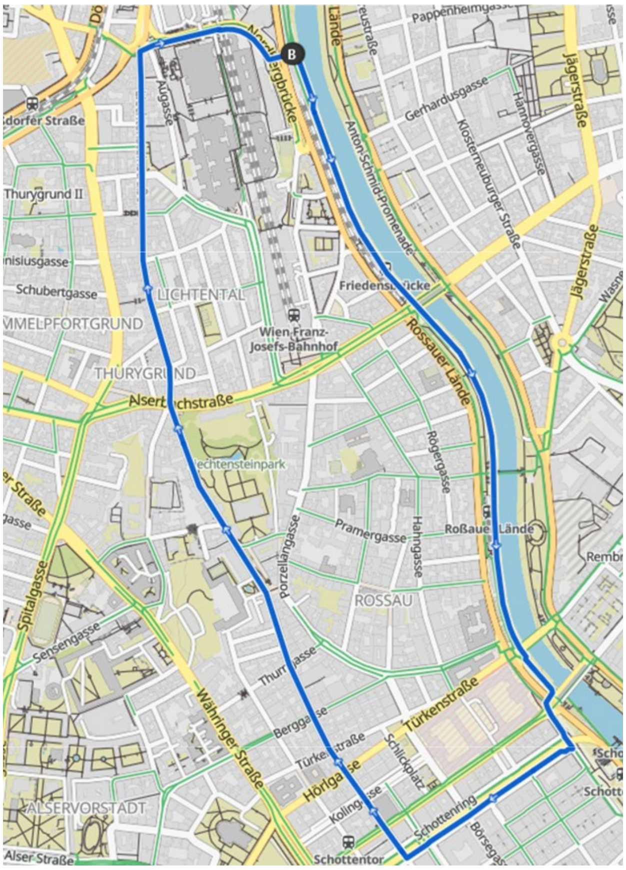

Figure 2. Route of the cycling task in Vienna.

The infrastructure designs and layouts of the sections varied in terms of surrounding buildings, tree cover and interactions with other road users (see figure 3). The mixed cycling lane shared with pedestrians (completely separated from car traffic, top/left) followed along the Danube channel with trees lining the channel side and along a stone wall on the other side for most of the section. The dedicated cycle path (top/right) also includes tree cover and is separated from car traffic and tram lines by a curb with green space and trees on both sides. The two sections where roads were shared with cars (on the bottom) are characterised by surrounding buildings on both sides of the road with the buildings being predominantly five to seven stories tall. In the section where the cycling traffic was separated from car traffic by a continuous line on the asphalt (bottom/left), the cycling lane in this section was situated between the moving traffic and parked cars.

Figure 3. Photographs of the cycling route.

For safety reasons, the route did not include sections where participants had to cycle along tram lines. In order to minimise the confounding effects of physiological responses as much as possible, i.e., due to changes in altitude, the route chosen has a limited ascent of 50 metres and a descent of 50 metres over a distance of 4.98 km.

A traffic census was also carried out prior to the study to determine the traffic volume of pedestrian, cyclist, and motorised traffic during different times of the day. Traffic data was collected over four days at approximately the middle point of each traffic segment for ten minutes at two different times within each time period. A significant difference in traffic volume was found between the timeframe of 13:00-15:00 and 16:00-18:00 local time. Based on the results of the traffic analysis, the former period was considered to be the off-peak traffic condition with lower overall traffic volume at all levels and the latter as the peak traffic condition. This is related to the second research question.

3.1.3 Recruitment

A total of thirteen participants were recruited. Due to errors in the measurement devices, data was only available for eleven participants of which six were female (55%) and five were male (45%). Participants were recruited using convenience sampling, including the staff of the Institute of Transport Studies at the University of Natural Resources and Life Sciences, Vienna, and the researcher's social network.

3.1.4 Instruments

For the route, participants were provided with an instrumented bicycle (see figure 4) and a safety helmet. A Raspberry Pi computer attached to the bicycle recorded time, braking, steering, and acceleration. A smartphone was mounted on the handlebar to collect GPS data (to determine speed and sections) and film the traffic events in front of the bicycle.

Figure 4. Instrumented bicycle with a smartphone attached to the handlebar and E4 smartwatch on the wrist.

Moreover, several devices have been used to collect the physiological responses of participants. These included an Empatica E4 smartwatch (see figure 5) to provide electrodermal activity (EDA)-data, and a Polar H10 chest belt for measuring heart rate (HR) and heart rate variability (HRV). Participants who were not reliant on wearing glasses were equipped with a VPS 19 eye-tracking device to determine pupil dilation, blink rate, fixation duration and fixation rate of the eyes.

Figure 5. Empatica E4 smartwatch collects physiological data in the form of EDA with sensors seen from two perspectives of the device.

In addition, a questionnaire was administered, based on the NASA Task Load Index (Hart & Staveland, 1988), and adapted for this study. Mental demand, physical demand, performance, effort, frustration levels and perceived safety were assessed on a 5-point scale. There are several shortcomings of retrospectively administered self-reports, e.g., being vulnerable to biases such as being reconstructions instead of actual reflections of previous states, differences in interpreting the questions etc. (Vanneste et al., 2021). Thus, pictures of different segments of the route have been taken to aid the reconstruction of the perceived load at different points of the route. To further support recollection of the different segments, people had to colour-code the previous variables on a map (with five different colours representing five different levels). The advantages of physiological measures are real-time measurements (Vanneste et al., 2021), and can measure cognitive load without interfering with the cycling task.

3.1.5 Procedure

At the starting point, participants were provided with an information sheet containing all the information regarding the tasks of the experiment, the measurement devices being used, and the route that had to be followed. As there is just one test bicycle, only one participant at a time could participate. After filling out the consent form, participants provided answers to a pre-questionnaire (see figure 6 for steps of the experimental procedure), assessing their suitability for cycling, basic demographics, and physical conditions, (i.e., amount of caffeine, alcohol, and tobacco consumed before cycling, as well as hours of sleep).

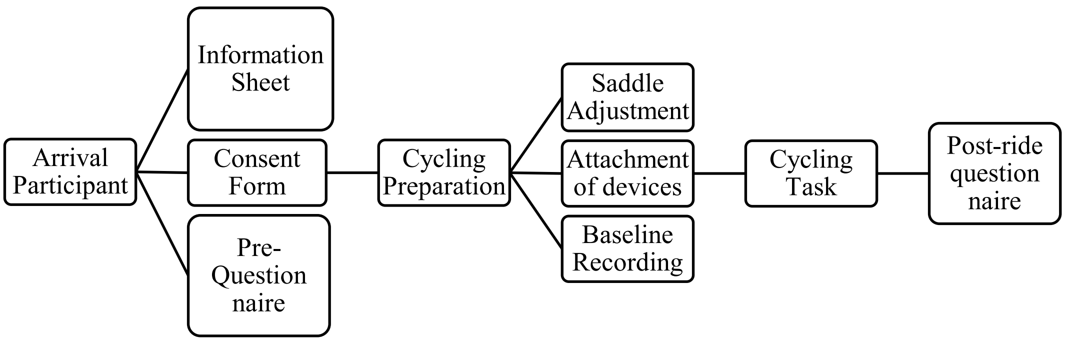

Figure 6. Overview of experimental procedure.

Then, the saddle height was adapted to the subsequent participants, and they were equipped with the physiological measurement devices. The route was reviewed again. Before the cycling task, participants had to stay in a resting state for three minutes to assess their baseline physiological responses as a reference for the active cycling part. Capturing the baseline response allows to put the physiological responses during the cycling part into perspective (see Buchwald et al., 2019). Participants were reminded to obey the traffic laws and cycle as they would do in their daily lives. For the cycling experiment, the researcher followed the participants at a distance of around 15 metres to ensure the correct route choice and to aid in case of any unforeseen situations due to the dynamic nature of traffic. Otherwise, there were no interactions for the duration of the cycling task. After finishing the ride, sensors were removed, and participants colour-coded their mental and physical demands, frustration, perceived safety, performance, and effort for different segments of the route, which assesses the factors of the NASA Task Load Index. Retrieval of memory was aided by providing pictures of different sections of the route.

3.2 Data Processing

Due to the limited timeframe of the thesis (15.01.2024-02.06.2024), time was not sufficient to analyse the heart rate data acquired from the Polar H10 chest belt and the eye-tracking data from the VPS 19 eye-tracking device and conceptualise them into a cognitive load index. Thus, the analysis focuses on the EDA-related data captured by the Empatica E4 smartwatch. Data had to be pre-processed before checking basic assumptions and running a statistical model (see Figure 7 for an overview of the research process).

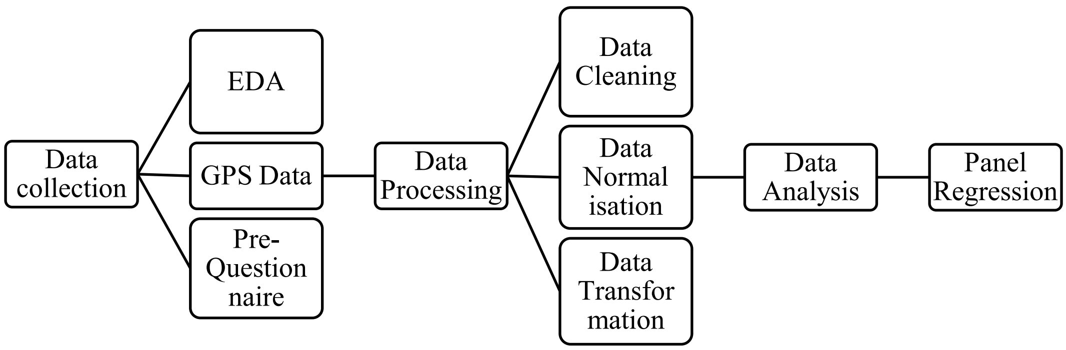

Figure 7. Overview of data collection, processing, and analysis.

The EDA data from the Empatica E4 smartwatch is sampled in micro-Siemens (µS) and should be in a range between 0 and 100 µS (empatica, 2020). If there were values beyond that threshold, the data was cleaned. Further, the sampling frequency of the smartwatch is 4 hertz, indicating one datum being collected every 250 milliseconds. Due to the nature of EDA data potentially fluctuating in frequency, steps should be taken to account for this. Thus, EDA has been averaged in five-second windows for each data point collected when moving and averaged to counter the frequency fluctuations, as typically done in other studies considering EDA (Picard et al., 2001, Caviedes & Figliozzi, 2018). The obtained moving averages are then used to normalise the EDA data based on the EDA mean in a resting state to be able to compare the EDA during the task, as conceptualised in other EDA studies (Healey, 2000, Caviedes & Figliozzi, 2018). This is further important because people vary in their physiological data and thus, comparing their responses during the task with the baseline takes into account their person-dependent profiles (Vanneste et al., 2021).

$$e_n = (e_a + e_m)/e_{m)}$$

e_n = normalised EDA signal
e_a = 5-second average for EDA data a while cycling
e_m = EDA baseline mean measured for three minutes before cycling

Using the method shown in the formula above has the advantage that the output for EDA data during the ride can be considered in relation to the EDA responses that each participant shows when in a resting state, which should represent the typical EDA response when in a calm state and not moving.

The first independent variable road design has been conceptualised and is represented by different sections that vary in their built environment conditions. The sections for the data analysis are based on GPS-specific ranges. Sections that represent the different traffic segments (built environment) have been determined on the different road conditions (path shared with pedestrians, bike path, road shared with cars, road shared with cars separated by a continuous line). The different sections can be seen in figure 8: Section 1, green line = mixed path with pedestrians. Section 2, orange line = dedicated bicycle path. Section 3, red line = road shared with cars. Section 4, purple line = road shared with cars but separated by a continuous line painted on the asphalt. The blue lines are the connection pieces between the different sections.

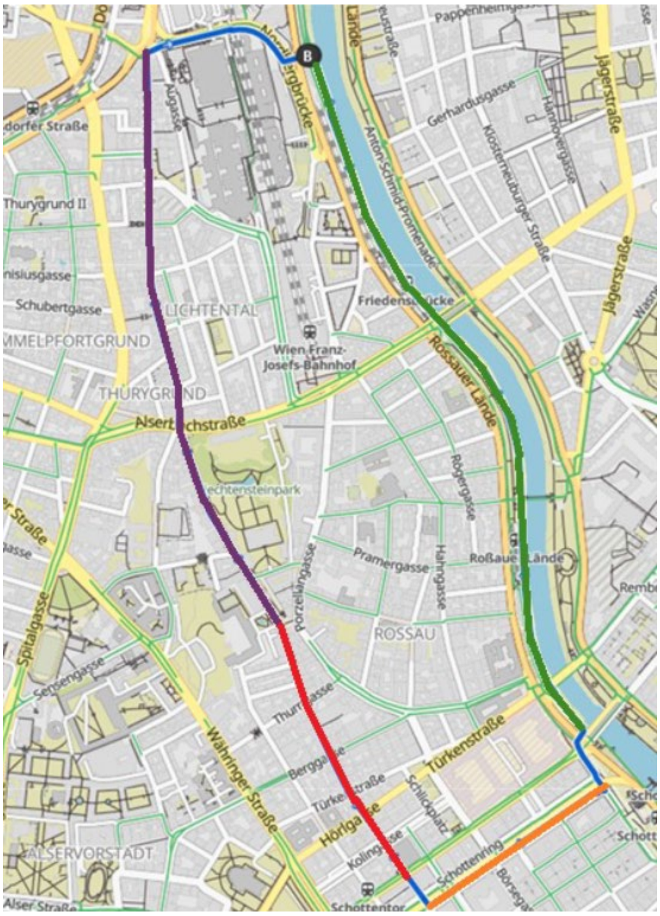

Figure 8. Different sections of the cycling route.

The sections have been determined based on GPS point ranges. For statistical analyses, the sections have been dummy-coded. Dummy coding is used in regression models when categorical variables are included, e.g., section, traffic volume, and gender (Alkharusi, 2012). A numerical value is assigned to a specific group, e.g., 1 to section 1 and 0 to all different sections (see table 1 for an example of dummy coding). For regression analyses, it is necessary to have quantitatively representable data, a feature that categorical variables do not inherently possess and thus are required to be transformed by dummy coding (Cohen et al., 2013, Alkharusi, 2012).

Table 1. Example of dummy coding section

Section 1	Section 2	Section 3	Section 4
1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1

The second independent variable traffic volume was assessed before the experiment phase took place. For the off-peak traffic volume condition, participants cycled between 13:00-15.00 local time and for the peak traffic volume condition, participants cycled between 16:00-18:00 local time. The traffic volume variable has also been dummy-coded for the analysis in the same scheme as displayed in Table 1.

While participants were not moving, e.g., at a traffic light or due to being behind cars that stopped on the road, GPS signals were still being sampled. Here, the occurrence of random errors was increased. The GPS errors could be due to the reflection of the signal by buildings, their blockage of the signal of the satellite orbit, or receiver application issues (Jun et al., 2006, Ogle et al., 2002, Zito et al., 1995). As the moving satellites created a cluster of GPS points close together, the data had to be cleaned (Jun et al., 2006). To account for this issue, GPS data has been visually inspected. If the speed of three consecutive points was below than 0.8 m/s or less, it was set to zero to account for errors in the GPS signal. The recorded videos of the test rides have been checked at respective points linked to GPS errors, to determine whether the odd GPS data is linked to situations like traffic light stops or other stops and have been confirmed.

Speed was the first control variable considered for the statistical analysis (see table 2 for an overview of independent and control variables). It has been calculated based on the GPS data that was sampled every second and the distance travelled to the next GPS point in a given second. Odd values of speed that occurred due to GPS errors with more than 10 m/s (36 km/h) have been filtered out. A study that was conducted in Vienna and other cities in Austria focused on capturing people’s movement data and considered the maximum speed for average cyclists in the urban context at 36 km/h (Schnötzlinger et al., 2022). Speeds above that threshold were considered not possible with the test bicycle having only one gear. As no significant downhill slope was present during the study route, speeds above that threshold were therefore filtered.

The slope is important to consider as it potentially influences physical demand leading thereby to higher EDA values. It has been calculated based on GPS points of longitude, latitude, and altitude. The changes in distance travelled per second and altitude changes are an indicator of slope. The slope had some unusually high values for some participants, which are due to errors in the GPS measurements. Outliers that were three standard deviations below or above the mean were removed.

In the pre-questionnaire, people indicated whether they consider themselves active cyclists or not, which provided further information about participants' cycling habits and experiences in the urban context. For the statistical analysis, active cycling has also been dummy-coded. Temperature data of the given day and time has been acquired on the website https://www.timeanddate.com/ (Date and

Time, 2024). The overall temperature range was between 11-23°C, and was coded into three temperature ranges, low: 11-14°C, medium: 15-19°C, and high: 20-23°C. Lastly, gender has also been dummy-coded into male and female participants.

Table 2. Description of independent and control variables

Independent/Control variables*	Description
Section (1, 2, 3, 4)	Different sections of built environment conditions
Run (1, 2)	Differences in traffic volume (peak vs off-peak traffic)
Speed*	Measured in m/s
Slope*	Continuous value indicating ascent or descent
Active*	People indicating being active or not active cyclists, dummy-coded
Temp*	Temperature, dummy coded into low (11-14°C), mid (15-19°C) and high (20-23°C) ranges.
Gender*	Male and female, dummy-coded

3.3 Data Analysis

To investigate the effects of one or several independent variables on a dependent variable, regression models are oftentimes used to showcase these effects. While simple linear and multiple regression models may be useful in certain instances, the analysis of this naturalistic study with repeated measures calls for a different statistical model to analyse the data. The aforementioned regression models for this study would produce biased estimates of the effects due to unobserved confounding variables (Brüderl & Ludwig, 2015).

A fixed effects regression can take these unobserved errors into account and deliver estimates that are unbiased (ibid.). Time series, or so-called panel data models are useful if each participant is observed chronologically and data is merged on top of each other (i.e., pooled) (Brüderl & Ludwig, 2015). The dependent variable is typically continuous, while independent variables can be measured in different scales. The fixed effects model especially takes the errors into account.

$$y_{it} = x_{it}\beta_1 + x_{it}\beta_2 + \cdots + \alpha_i + \epsilon_{it}$$

In the formula above, y is the dependent variable, in this case, the observed EDA value of participant i at time t. β_1 is the coefficient of the independent variable 1 level 1 (i.e., road design 1). α_i is the first error term that relates to characteristics specific to each participant that are time-constant and cannot be observed by the researcher (e.g., personality, resilience in traffic) but still affect the covariates. The α_i replaces α which in standard regression models is seen as the intercept and would lead to collinearity issues with the first error term. ϵ_{it} is the second error term, also called idiosyncratic error, which accounts for the variability across time and participants (Brüderl & Ludwig, 2015).

The two error terms can be identified through panel data as participant characteristics can be assumed based on the repetitive observations. Thus, a panel regression model with fixed effects was used for the acquired data to test the relationship between road conditions, traffic volume and cognitive load, measured through EDA.

4. Results

4.1 Relation to Research Questions

This study aimed to better understand the influence of the built environment on cyclists. More specifically, the scope was to investigate the influence of different traffic segments and traffic volume on the cognitive load experience of cyclists in Vienna, Austria. The first research question aimed at understanding the differences of road segments on cyclists' cognitive load, with participants cycling on a dedicated cycle path, on paths mixed with pedestrians, on roads separated from car traffic with a continuous line and on roads in between cars. The second research question was aimed at understanding the differences in traffic volume (i.e., peak vs off-peak traffic) on cyclists' cognitive load.

4.2 Descriptive Statistics

The average speed of the participants was 13.51 km/h with a standard deviation (SD) of 7.47 km/h. The mean time participants needed to cover the route was 00:19:58 with a range of 00:16:14-00:25:11.

After outliers of the EDA data (dependent variable) have been removed, the EDA data has been normalised (see Equation in Chapter 3.2). The overall mean response of normalised EDA was 1.76 with a SD of 3.06. The different distributions of the normalised EDA based on the road-geometric infrastructure designs can be seen in Figure 9. Normalised EDA responses were skewed to the right with the lowest ranges in the condition mixed bicycle path (shared with pedestrians; see figure 9. top/left) and the highest ranges for the condition mixed cycling traffic on roads with cars (separated by a continuous line; figure 9. bottom/right).

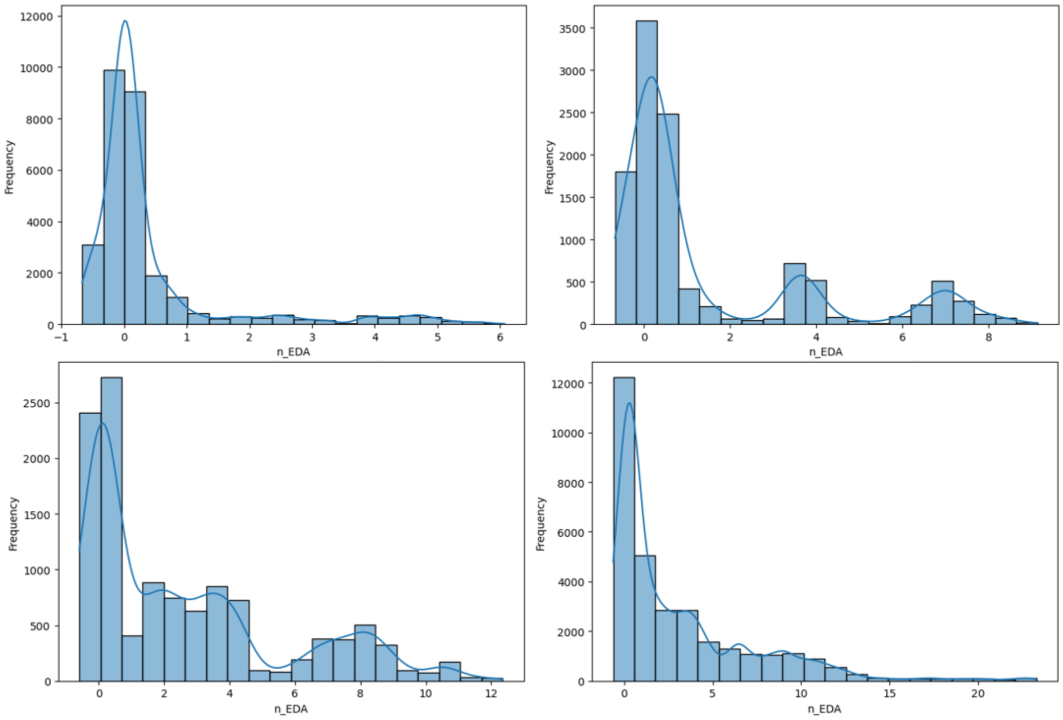

Figure 9. Histograms of normalised EDA distributions: from upper left in clockwise direction; section, 1, 2, 3, 4.

For most participants, the residuals are approximately normally distributed (see figure 10). The variability in the individual-specific effects is moderate, with residual values of Participant 7 being skewed to the right, indicating that this participant showed a larger random effect than expected, meaning an individual-specific deviation of EDA from the average.

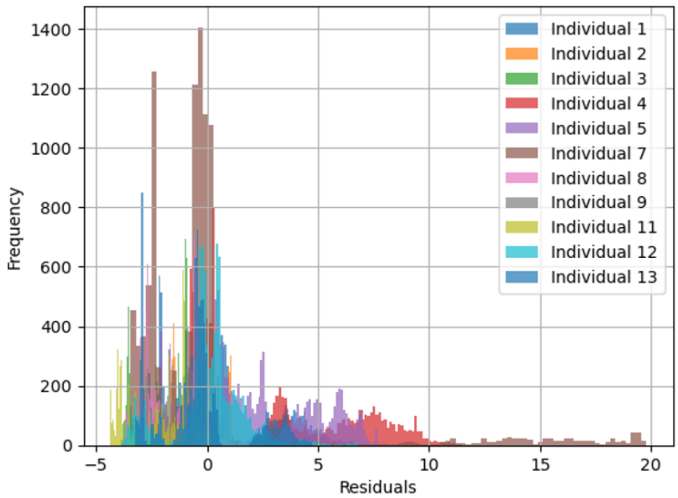

Figure 10. Distribution of individual-specific random effects regression model

A fixed effect panel regression was applied to test the hypothesis of whether road design and traffic volume differ in their influence regarding their varying levels of cognitive load measured by EDA. Issues of multicollinearity have been checked through the Variance Inflation Factor (VIF). VIF values of all independent variables are well below 10, indicating that the independent variables are not highly correlated with each other, i.e., showing no violation of multicollinearity. The explained variance, R^2 indicates how much of the variance of the dependent variable can be explained by the independent variables. In this case, R^2 equals 27.85%. This value indicates that 27.85% of the normalised EDA variable can be explained by the model.

Table 3. Parameter estimates, $R^2 = 0,2785$.

Coefficient	Parameter	Std. Err.	t-value	p-value
Intercept	2.6252	0.0355	73.897	< .001
Section 1	-0.9372	0.0301	-31.094	< .001
Section 3	1.2083	0.0347	34.845	< .001
Section 4	1.7419	0.0291	59.864	< .001
Run 2	-0.6526	0.0164	-39.847	< .001
Speed	-0.0522	0.0048	-10.971	< .001
Slope	0.0649	0.0205	3.1656	< .01
Active	-2.2544	0.0192	-117.50	< .001
Temp_low	1.7411	0.0246	70.906	< .001
Temp_med	0.1808	0.0193	9.3482	< .001
Gender_female	0.7734	0.0173	44.636	< .001

As it was hypothesised that people cycling on the bike path would show the lowest cognitive load, it has been included in the intercept of the regression model (see table 3 for an overview of the parameter estimates). For the traffic volume conditions (reflected by variable run 1 and run 2), run 1, reflecting the off-peak traffic condition has also been included in the intercept. The other sections and run 2, representing the peak traffic condition, have been included in the model. Contrary to the first hypothesis, people during the mixed bike path with pedestrians showed a lower normalised EDA response, than on the dedicated cycling lane, $t(-31.09) = -0.94$, $p < .001$. Participants on roads shared with cars and no line showed a higher normalised EDA response $t(34.84) = 1.21$, $p < .001$. Participants on the roads shared with cars and separated by a line showed a higher normalised EDA response than on the dedicated cycle lane $t(59.86) = 1.74$, $p < .001$. That is also higher than the road condition shared with cars without a line.

Also, contrary to the second hypothesis, participants in the high traffic volume condition show a lower normalised EDA response compared to the low traffic volume condition $t(-39.85) = -0.65$, $p < .001$.

Control variables of slope $t(3.17) = 0.06$, $p < .01$, active $t(117.5) = 2.25$, $p < .001$ and gender $t(44.64) = 0.77$, $p < .001$ are also significantly influencing the EDA response, with females showing a higher EDA response than males. Higher speed is linked to a lower EDA response $t(-10.97) = -0.05$, $p < .001$. The lowest temperature range 11-14°C showed the highest EDA response $t(70.91) = 1.71$, $p < .001$, and the middle-temperature range 15-19°C also showed a higher EDA response $t(9.35) = 0.18$, $p < .001$, compared to the high-temperature condition 20-23°C.

5. Discussion

The present study aimed to investigate the influence of different traffic conditions on cyclists' cognitive load in the context of Vienna, Austria. For that, physiological measurements have been used as an indicator of cognitive load, more specifically normalised EDA data of the Empatica E4 smartwatch, which have been validated as an indicator of cognitive load (Ayres et al., 2021). It was hypothesised that different traffic conditions vary in their influence on cyclists' cognitive load, with cycling on a dedicated cycling lane eliciting the least cognitive load response and cycling on the road shared with cars without a separation of a line eliciting the highest cognitive load response. In addition, as participants cycled twice, one time during peak traffic and one time during off-peak traffic, the former conditions were hypothesised to elicit higher cognitive load responses.

In contrast to the first hypothesis, the cognitive load experience in the dedicated cycling path condition has shown a higher response than in the mixed path with pedestrians, which could be due to the layout of the cycling path. It involved an interrelation with motorised traffic including several intersections with traffic lights. As expected, the cycling path condition showed a lower cognitive load response as in the two conditions where the road was shared with cars. Nonetheless, the road condition where participants were separated from cars with a continuous line painted on the asphalt showed a higher cognitive load experience compared to the condition where the road was shared with cars without any separation.

Further, in contrast to the second hypothesis, overall, participants showed a lower cognitive load response during the high-volume traffic condition compared to the low-volume traffic condition.

5.1 Comparison with Previous Studies

Research has shown that the built environment influences the likeliness of people to choose the bicycle as a mode of transport (Gössling et al., 2019b). Concerns regarding safety, comfort, and the interrelation with car traffic are important aspects to consider when aiming at increasing the modal share of cycling (Aldred, 2013). Previous studies have looked at built environment conditions and stress in the context of North America and validated EDA measures in naturalistic studies

(Caviedes & Figliozzi, 2018). Others have investigated the effect of cognitive load on cycling in virtual environments (Guo et al., 2022). To this date, the current study is one of the first which considers the impacts of the built environment conditions, defined by varying road infrastructure designs as causal factors on the cognitive load of cyclists in a naturalistic way. Investigating these influences adds to the research by providing information about how the infrastructure designs differ in their influence on cognitive load and perceived safety thereby adding to the understanding of the needs of cyclists in urban traffic.

5.2 Limitations

This study has several limitations. In a naturalistic study, the variables of interest cannot be controlled to the same degree as in a laboratory study. City traffic is dynamic and changes constantly. Thus, for the participants who cycled at different times, traffic situations were always at least slightly different. Examples of the dynamic nature of traffic include an accident involving a pedestrian and a car which certainly influenced the cognitive load experience of the cyclist. Further, a car crossed the line that separated bicycle traffic from car traffic and required the participant to stop and wait, which also significantly influenced the cognitive load experience.

In addition, while traffic volume was determined before the start of the experiment, there have been instances where participants experienced different situations, e.g., if a bus was cycling behind the participants during peak traffic in the section where the road was shared with cars, the bus and the following cars have often not been able to overtake and thus creating a more calm traffic situation for the participant. In contrast, during the off-peak traffic, participants could find themselves in more dynamic traffic situations.

In relation to the second research question, the majority of participants cycled the route first during the off-peak traffic condition. Several participants reported the influence of the familiarity of the route and how it affected their concentration levels and perceived cognitive load. Harms et al. (2021) showed that familiarity with travel routes affects the cognition and behaviour of traffic participants, including cyclists, in urban settings by reducing task difficulty and the required cognitive control needed for navigating in traffic. Relating to this study, participants may thus have perceived a lower cognitive load in the second run during the peak traffic condition as they felt more familiar with the route and did not need to concern themselves as much with the route navigation anymore. Thereby uncertainty of what to expect from the study route was removed. Furthermore, not all participants were residents of Vienna and thus not familiar with the city and traffic dynamic itself, which poses further difficulty in navigating and subsequently increasing the demand on cognitive load compared to those who have been living in Vienna for some time. While familiarity has not been considered for the data analysis, it constitutes an important factor that should be considered in future research.

A few participants reported profound experience with cycling in urban traffic and did not consider the different segments as varying in their impact on cognitive load or that higher traffic volume would affect them more. That could be explained by previous research, which has shown that more experienced cyclists are less affected in their level of comfort when cycling along motorised traffic during their commute (Stinson & Bhat, 2004).

Temperature data could also not be controlled. The timeframe for the data acquisition was planned to be as short as possible. Due to several factors, the time for data collection extended beyond the initially planned timeframe. As the time to participate required cycling twice, availability of consecutive days was not always given, leading to a spread of data collection over many weeks. Further, during the easter break, data collection was postponed due to uncertain changes in traffic volume. As the study route passes a school, the traffic situation would have changed dramatically. Also, due to the shift from winter to spring, the temperature range was between 11-23°C. Results suggest higher EDA response at lower temperatures. While it appears counterintuitive, it could be due to clothing, as more layers were worn at lower temperatures, where thermal insulation and reduced sweat evaporation are associated with layers of clothing (Gavin, 2003, Corbett et al., 2015).

Another factor that may have influenced the results is the choice of the experiment route with different characteristics of the four sections. Nawrath et al. (2019) showed the influence of urban green infrastructure and how it positively affects people's willingness to cycle. While both sections separated from car traffic included tree cover, the section shared with pedestrians followed along the Danube channel. Previous research showed that exposure to water in urban areas has a positive effect on reducing stress levels (Ulrich et al., 1991). Consequently, the calming effects of the water while cycling may have influenced the cognitive load experience of the participants, potentially explaining the lower response compared to the dedicated cycling lane.

Participants in the section that was shared with cars and separated by a line from motorised traffic felt less safe compared to the section without the separation, due to the fear of dooring (i.e., doors of parked cars opening when passing). As a previous study regarding safety perceptions in mixed bicycle and motorised traffic has shown (Chataway et al., 2014), cyclists reported feeling unsafe in traffic situations where they are "sandwiched" between parked cars and motorised traffic.

Wind data has not been considered as a factor influencing the physical demand possibly affecting EDA measurements but could be an additional influencing factor. There have been some wind gusts at times in the first segment representing the traffic condition with the bike path mixed with pedestrians, along the Danube channel.

The sample size (n = 11) was small which can be explained by the complexity of the study and the time it took to prepare the route, materials, and the time each participant needed to complete the two runs including briefing and debriefing. The inference based on the data could be improved by having a larger sample size. Thus, the generalisability to a larger population of the study is limited.

Lastly, based on the data, some participants are more predictable than others as can be observed in the residual distribution of their normalised EDA values (see Participant 7 in Figure 9). Potential influences might be personality traits, for example how people react to certain traffic events.

5.3 Future Research

This study contributed to research by investigating the differences between several road infrastructure designs and traffic conditions on the cognitive load of cyclists, measured by normalised EDA. Future research should provide a more holistic assessment of cognitive load by analysing further physiological measures of cognitive load that provide more detailed information, e.g., eye-tracking data. Eye-tracking data in addition to EDA data measures cognitive processes through the focus of the eyes and thereby shows a more holistic assessment of cognitive load (Ayres et al., 2021).

Furthermore, the route of 4.98km had four different built environment conditions. Future research should let participants cycle in a variety of different infrastructure designs to learn more about the influences that were not covered by these designs. An important aspect for cyclists was familiarity with the route. As familiarity affects the task difficulty in traffic, it is something future studies should consider. It was reported by several participants that it affected their concentration and perceived cognitive load. Furthermore, this study did not take specific events within each section into account. The dynamic nature of traffic can influence cognitive load through numerous factors. To learn more about the specific aspects of the different infrastructure designs, events within those designs should be considered. Eye-tracking data combined with a video analysis of the ride would enable the consideration of specific events that trigger high cognitive load responses that are influenced by traffic events. So, urban planning strategies can account for those situations and prevent them by making changes to the built environment conditions.

Lastly, including human factors, such as personality traits, allows to gain insight into how people react differently to the same situations and what aspects of the built environment are shared by people with different personality dispositions, thereby highlighting its overall importance.

6. Conclusion

The transport sector is responsible for the second highest level of GHG emissions after the industry sector, with car traffic accounting for a large proportion of the transport sector's emissions. Many European cities are therefore setting plans for more sustainable city planning, with a particular focus on cycling infrastructure.

One contribution of this study for research is the use of EDA as a measure of cognitive load for cyclists in different traffic environments. The results provide information on how the differences in traffic conditions induce different levels of cognitive load for cyclists and which road conditions are thus more suitable for creating a safe infrastructure for cyclists.

The results suggest that cycle lanes that are physically separated from motorised traffic, either as dedicated cycle lanes or mixed paths with pedestrians elicit lower cognitive load and should therefore be favoured in urban infrastructure planning.

Although not all hypotheses were confirmed, the results contribute to the knowledge regarding the cognitive load experienced by cyclists and highlight the differences between built environment designs in which cyclists have to share the roads with cars and where they are separated from car traffic by built environment elements.

One possible application of the findings of this study for urban planners and policymakers is to design more bicycle-friendly infrastructure that is physically separated from motorised traffic. Further research could use larger sample sizes as well as replicate the study in different cities.

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Popular science summary

Cycling offers a range of benefits to those who cycle, including health, social and economic advantages. It is a form of transport that requires little to no greenhouse gas emissions and can provide a good transport option for urban transport in light of global warming.

Many European countries are aiming to increase the proportion of people who cycle. To encourage people to choose cycling over motorised vehicles in urban areas, it is important to consider factors of the built environment. To understand the influence of the built environment and traffic situations better, this thesis focuses on the cognitive load of cyclists.

Cognitive load can be understood as the mental cost of performing tasks and is a limited resource. It has an influence on the behaviour and perceived safety in traffic, which further influences the likelihood of people choosing the bike as a mode of transport. Therefore, understanding the differences in built environment conditions on the cognitive load of cyclists, provides information about what factors are important for urban planning strategies for traffic.

This study measures the cognitive load of cyclists not in the laboratory, as in many previous studies, but in a naturalistic way in the real-world context in the city of Vienna, Austria. Statistical measures are used to understand the differences between the different traffic segments and the volume of traffic. The results show that cyclists have lower cognitive load measures when they are physically separated from car traffic, either on mixed pathways or on cycle lanes that include built elements separating bicycles and cars. When cyclists are required to share the road with cars, their cognitive load levels are higher. The highest cognitive load response is observed when cyclists are cycling on a lane between car traffic and parked cars, separated by a line painted on the asphalt.

The findings help to understand what traffic segments lead to higher cognitive load levels of cyclists and therefore can be considered by urban planners and policymakers when working to improve the built environment conditions for people cycling in the urban context.

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