HHS Public Access
Author manuscript
Transp Res Interdiscip Perspect. Author manuscript; available in PMC 2023 May 11.

Published in final edited form as:
Transp Res Interdiscip Perspect. 2022 December ; 16: . doi:10.1016/j.trip.2022.100703.

A Naturalistic Study Assessing the Impact of Daytime Running Lights and Vehicle Passing events on Cyclist's Physiological Stress

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Abstract

Bicyclists are vulnerable road users who are at a greater risk for injury and fatality during crashes. Additionally, the "near-miss" incidents they experience during regular trips can increase the perceived risk and deter them from riding again. This paper aims to use naturalistic bicycling data collected in Johnson County, Iowa to: 1) study the effect of factors such as road surface type, parked vehicles, pavement markings and car passing events on cyclists' physiological stress and 2) understand the effect of daytime running lights (DRL) as an on-bicycle safety system in providing comfort to cyclists and highlight of their presence on the road to other vehicles. A total of 37 participants were recruited to complete trips over two weekends, one weekend with DRL and the other without DRL. Recruitment was specifically targeted toward cyclists who expressed discomfort riding in traffic. Data were collected using a front forward facing camera, GPS, and a vehicle lateral passing distance sensor mounted on the bicycle and a Empatica E4 wrist band (providing physiological data such as electrodermal activity; EDA) worn by the cyclist. Data from those sources were cleaned, processed, merged, and aggregated into time windows depicting car passing and no car passing events. Mixed effects models were used to study the cyclists' skin conductance response (phasic EDA) and baseline skin conductance level (tonic EDA). Car

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passing, parked vehicles, and roads with dashed centerline markings were observed to increase the cyclists stress. The use of DRL had negligible impact on cyclist stress on roads.

Keywords

Perceived risk; Daytime Running Lights; Car Passing Events; Electrodermal Activity; Safety; Bicycle

1. Introduction

Cycling is a popular recreational activity, often adopted to increase overall health and reduce cardiovascular risk (Hamer and Chida, 2008). Cycling has often been considered a standard means of transportation, however, the ridership rates have neither consistently increased or decreased over the years (Reid, 2017). Even among the European countries where it is a common mode of transportation today, the current ridership rate falls far below the historical records (Oldenziel et al., 2016). In addition to local interest and the growing bicycle market, governments have played an essential role in shaping policies that enhance cycling safety and convenience (Dill, 2009). Bicycling has numerous advantages ranging from personal health benefits (Ming Wen and Rissel, 2008) to significant positive environmental impact. It is a greener commute option that effectively reduces vehicle emissions and combats traffic congestion: two of the biggest urban transportation problems (Sener et al., 2009).

In the past decade, bicycling has grown into a popular mode of transport in the United States for daily commuters (Sanders, 2015). Micromobility has been a vital factor quietly advancing the biking industry with its shared services that include fully or partially human-powered vehicles such as bicycles, e-bikes, and e-scooters. As reported by the National Association of City Transportation Officials (NACTO) (National Association of City Transportation Officials, 2020), before the pandemic in 2019, over 50 million bicycle trips were recorded on shared bikes and e-bikes, the highest since 2010. This increase in ridership was fueled by more bikes, dock stations, and the miles of slower streets available for cycling. Particularly in larger cities, bike-sharing systems have been established such as Citi Bike in New York City, Divvy in Chicago, and Blue bikes in Greater Boston that provide a greener and healthier alternative for commuting (Todd et al., 2021). However, the lack of adequate cycling infrastructure or public transportation in many states of the country makes driving the only available transit option (National Association of City Transportation Officials, 2020).

Bike ridership has increased, yet not as a competitive commute option against motor vehicles. Porter et al., 2020 analyzed data from the 2017 National Household Travel Survey (NHTS) that highlighted lack of safety and infrastructure accommodations, and heavy motorized or pedestrian traffic as the significant barriers to bicycling. There are two kinds of risk for cyclists in the traffic environment: the objective risk (in terms of fatalities and injuries) and the perceived risk (how risky they think cycling is) (Aldred et al., 2015). Objectively, cyclists are at a greater risk for injury or fatality through crashes because they do not have the same protection as an occupant of a motor vehicle to absorb the impact of a crash (Yannis et al., 2020).

Before the pandemic in 2019, the National Highway Traffic Safety Administration (NHTSA) reported that 843 bicyclists were killed in crashes, accounting for 2% of all motor vehicle crashes (National Highway Traffic Safety Administration, 2020). Since 2010, approximately 1–2% of all traffic crashes involving bicyclists have been fatal, whereas only 0.5% of all traffic crashes involving motor vehicles have been fatal (NHTSA, 2020a, 2020b). Besides fatalities, it is crucial to consider the "near-miss" incidents that can increase the perceived risk involved in cycling that can strongly deter a cyclist from taking it up as a commute option in the future (Aldred and Crosweller, 2015). Cyclist safety has often focused on reducing the objective risk with measures such as wearing safety gear or protected bike lanes. Although this reduces the number of bicycle fatalities, it does not significantly increase ridership (Aldred et al., 2015). It is essential to alleviate the perceived risk involved in cycling to encourage ridership in the future ("Fear of Cycling," 2020).

Recent research has changed direction to focus on the near misses and non-injury incidents that cyclists may impact a cyclist's perceived risk and often prevent them from taking up the next ride (Aldred and Crosweller, 2015; Sanders, 2015). This paper aims to understand cyclist stress as measured by physiological response experienced during cycling using naturalistic data. Physiological signals of the cyclist were recorded in real-time during trips while collecting other information such as traffic videos and lateral distance between passing vehicles and the cyclist. Heart Rate Variability (HRV) and Electrodermal Activity (EDA) are considered good indicators of stress as the Sympathetic Nervous System directly influences them during stressful situations (Empatica, 2018). Electrodermal activity measures skin conductance and is a popular physiological stress biomarker (Boucsein et al., 2012). Video, GPS, and lateral distance data were analyzed to identify environmental factors and traffic events and their impact on the cyclist's physiological stress. Additionally, this paper also examines the effect of Daytime Running Lights (Madsen et al., 2013), a type of on-bicycle safety system marketed as providing a sense of security to the cyclist.

2. Cycling and Stress Research Background

Cycling is often encouraged to lower the risk for heart diseases, control type 2 diabetes, lower hypertension, and relieve mental stress (Oja et al., 2011). These benefits are further enhanced when cycling is a frequent commute option (Oja et al., 1991). However, heavy traffic, dangerous motorist behavior, and unsafe road infrastructure can all increase the cyclist's risk causing the commute to be more stressful (NHTSA, 2018). Cycling can be truly healthy only if the perceived and objective risk to the cyclist can be identified and eliminated (Aldred and Crosweller, 2015). Hence, it is imperative for traffic safety research to identify risk factors from the traffic environment and eliminate them to ensure the cyclists have a safe and stress-free biking experience.

Prior research has assessed risk for cyclists using different methods such as surveys or questionnaires, analysis of crash databases, and simulation studies. These methods are very different in their perspective on risk for cyclists. Crash databases are useful for assessing the objective crash risk cyclists face on-road and include a record of events with consequences such as fatalities, injuries, or property damage (Boufous et al., 2012). However, crash data does not include events that may have been stressful but did not result in a crash. On the other hand, surveys and questionnaires can capture subjective stress and perceptions of safety or risk felt by the cyclist during a trip (Chaurand and Delhomme, 2013; Sanders, 2015). Both these data collection methods are retrospective, that is, they are recorded after the event. A cyclist might have felt the risk at the moment, but in hindsight, such incidents may not be recalled as risky events. The major drawback of such methods is reporting bias and missing information (Johnson et al., 2010). Particularly with questionnaires, bias might occur due to cyclists hesitating to report safety-critical and stressful events caused by themselves (Werneke et al., 2015).

Simulation studies aim to recreate scenarios from the real-world and assess cyclist behavior in a controlled environment (Hughes and Harkey, 1997). Simulation studies often involve designing critical events, traffic volume, and infrastructural elements such as traffic lanes and parking to simulate real-world conditions and observe the behavior of the cyclist (Cobb et al., 2021). Such studies may be coupled with questionnaires that investigate cyclists' perception of risk or safety through different scenarios (Nazemi et al., 2014). However, lack of immersion can cause participants to not elicit their real world behavior. Also, it is difficult to encode the perception of risk due to near-misses as the danger is not real. Naturalistic studies offer a solution to overcome these limitations. They involve passive data collection where the cyclist is completely immersed in their environment. Naturalistic driving studies have helped extract critical information about the traffic environment and driver behavior by monitoring the driver's natural settings (van Schagen and Sagberg, 2012; Venkatachalapathy et al., 2022).

Recent naturalistic studies focus on real-time passive data collection in the case of cyclists. They involve deploying different devices such as cameras and sensors to capture the vehicle characteristics, traffic environment, and trip trajectory. Dozza and Werneke, 2014 collected naturalistic cyclist data to identify safety critical events. A total of 16 participants were recruited and asked to ride a bicycle equipped with a forward video camera, two brake force sensors, GPS, two inertial measurement units, and a push-button at the handle for the participant to indicate any critical event during their trip. Later they were interviewed to discuss the critical events they experienced. Another notable naturalistic study of cyclists was carried out in Japan by Yamanaka et al., 2013 using a probe bicycle developed to collect data on cycling speed, steering, braking, lateral distance, and vertical acceleration. Video data were also collected to understand the environment, and participants were asked to complete a survey to report their perception of safety and comfort during the trip. Debnath et al., 2018 adopted a slightly different approach to record real-time data of cyclists by mounting cameras on roadside structures. Video data collected was used to observe compliance rates of passing distance laws among passenger vehicles and identify demographic factors that could influence them. These studies were instrumental in highlighting the feasibility and benefits of naturalistic data collection for studies surrounding cyclist behavior and safety. Although these studies offer a real-time view of the traffic conflicts for a cyclist, they still addressed the risk perception in a retrospective manner through surveys and interviews, which is open to bias, as discussed earlier. Besides the safety aspect, naturalistic studies have also been used to understand the difference in behavior and safety between conventional cyclists and e-cyclists (Langford et al., 2015; Schleinitz et al., 2017).

Collecting real-time physiological data alongside other data sources in a naturalistic study allows us to capture the cyclist's perceptive risk in a minimally invasive and passive manner, overcoming the drawbacks of retrospective recollection. The belief is that the cyclist will experience physiological stress when they experience an uncomfortable or dangerous situation on-road and their sympathetic nervous system is pushed into a flight/ fight mode, initiating different reactions within the body. Zeile et al., 2016 conducted a small scale field study in Cambridge, Massachusetts, recording cyclist physiological data such as Electrodermal activity (EDA or skin conductance), heart rate variability (HRV), and skin temperature in real-time. By mapping the peaks in physiological data to the cyclist's subjective observations via an app they aimed, to identify points in an urban environment that elicit emotions such as fear or anger. However, they dealt with a small sample size (12 participants), most of whom had extensive experience driving in Boston traffic conditions.

Caviedes and Figliozzi, 2018 studied cyclists' physiological stress biking on different facilities during peak and off-peak traffic times. It was a novel approach to analyze cyclist EDA from real-world trips and identify significant traffic factors impacting. Although this study included cyclist's with varied level of experience, the sample size was very small (5 participants) and they were requested to follow a designated route. Ryerson et al., 2021 recorded biometric data (eye or head movement) of cyclist in real-time during their trips along a specific route with a protected cycling lane. The authors investigated the relation between infrastructural design and cyclist behavior to identify elements that enhance their perceived risk. Teixeira et al., 2020 conducted a similar study to investigate the effects of urban environment on cyclist's stress. The authors used skin conductivity and skin temperature data of different cyclists from 5 different cities in Europe recorded while they rode along a standard route.

With such past studies the focus has often been on the impact of traffic and infrastructure parameters such as peak traffic, intersections on cyclist's stress or perceived safety while controlling certain factors of the environment by specifying the route for travel. Overall, these studies indicate that physiological parameters can be a powerful tool to identify unsafe places for cyclists in the urban traffic environment. In this paper, the authors describe a truly naturalistic study allowing the cyclists to complete trips of their choice during different weekends. They are simply equipped with instruments to collect data in real-time. Furthermore, the study is conducted with 37 participants who are not particularly comfortable cycling in order to truly capture the elements that might deter them from riding again. Besides, infrastructural elements, this study also aims to understand the impact of vehicle passing and use of DRL on cyclist stress by capturing their physiological data during these events in real-time.

Among the different physiological parameters, Electrodermal activity (EDA) which measures skin conductance has become a popular physiological stress biomarker (Boucsein et al., 2012). In response to an external stimulus such as cognitive or physical stress or excitement, the sympathetic nervous system stimulates an increase in sweat production, especially in areas of the body with a high concentration of sweat-producing cells such as wrists, palms, and feet (Andreassi, 2010). Sweat production increases the moisture on the epidermis that can be detected as a change in skin conductance potentials (Christopoulos et al., 2019). EDA can be influenced by other environmental conditions such as temperature, humidity, and wrist movement. Therefore, EDA signals are typically corrected to account for environmental conditions and artifact defects (Boucsein, 2012).

Wearable devices such as the Empatica E4 can measure EDA by passing a small current between two electrodes in contact with the skin. The EDA signal has two components – tonic (Skin Conductance Level - SCL) and phasic (Skin Conductance Response - SCR) (Christopoulos et al., 2019). Figure 1 shows the EDA components where the circled part indicates the phasic EDA, and the straight incrementing line is the tonic EDA. The tonic component refers to the baseline EDA when no external environmental stimuli are present. The tonic component is the lowest EDA value within a time interval. Phasic activations are rapidly changing peaks observed in the EDA signal response to an external stimulus. It is beneficial to index Skin Conductance Response (SCR) to external stimulation, known as an Event-Related Skin Conductance Response (ER-SCR), to help rule out extraneous environmental conditions.

Learning from the reviewed literature, the authors designed and conducted a truly naturalistic study with little to no control on the participant's cycling behavior and stress response. Thus, 37 participants were requested to ride bicycles on two weekends equipped with a forward camera, lateral passing distance sensor and daytime running lights, and wrist-mounted physiological sensor. The authors aimed to assess the impact of different environmental variables (parked vehicles, pavement marking, surface type), car passing, and the use of Daytime Running Lights (DRL) on the cyclist's physiological stress. A significant contribution of this study is the dual model approach analyzing the cyclist's SCR and SCL independently allowing us to observe individual factors and their lasting impact on cyclist's stress. This comprehensive study aims to understand a holistic picture of events in the real world and the subsequent physiological response they elicit in the cyclist.

3. Methods

3.1. Data Collection

Thirty-seven participants participated in this naturalistic bicycling study based in Johnson County, Iowa. Participants were recruited based on their comfortability for riding bikes in traffic. On a scale of 1 to 10, 1 being least comfortable and 10 being highly comfortable, participants who self-reported a score of 6 or lower were selected for the study. They were randomly assigned either an intervention (DRL) or control group and requested to ride their bicycles on two separate weekends. Half of the participants in the intervention group rode their bicycle with DRL attached during the first weekend only and the other half of the intervention group rode with DRL on the second weekend only. The control group rode both weekends without DRL. Participants completed baseline questionnaires which gathered demographic and bicycle riding experience information. Participants were also asked to keep written trip diaries recording the date, time of day, trip purpose, a self-reported comfort rating, and details on any crashes, near crashes, or anything that made them feel unsafe during the ride. Participants were given $25 Amazon gift cards after the first weekend of participation and their choice of a second $25 gift card or a Bontrager Flare R City rear light (MSRP $39.99) at the end of their second/final weekend of data collection.

A total of 88 hours of trip data was collected from three devices physiological data from wrist-mounted Empatica E4, GPS trajectory and video data from GPS-enabled cameras mounted on the bicyclists' handlebars (Contour GPS), and an ultrasonic lateral passing distance sensor. The GPS data provided the path of travel at 1 Hz frequency. The forward camera attached to the bicycle handlebar captured information about the environment, route, and behaviors during the trip. The vehicle lateral passing distance sensor indicated the lateral distance of any nearby vehicle to the bicyclist. The sensor is set to a default value of (290–300 inches) in the absence of a vehicle and then decreases steeply when a vehicle is in close proximity. Each participant wore an Empatica E4 wrist band which recorded their physiological data during the trip. The E4 band collects five types of physiological data – Skin temperature, Electrodermal activity, Blood volume pulse (BVP), Heart rate (HR), and Interbeat Interval (also known as Heart rate variability).

3.2. Video Coding

The traffic videos collected from each trip were manually coded to extract the roadway surface type, car passing events, pavement markings, and parked vehicles during each cycling trip. Participants were asked to complete trips along their desired routes during the study period. Hence, seven types of surfaces were identified through the recorded traffic videos. Figure 2 shows the different surface types coded. Among the different surface types, the focus of our analysis lies on Shared Roadway (Street Facilities) and Bike Facility.

The percentage of parked vehicles were continuously coded throughout each trip into three categories – 0–25% Parking covered, 25–75% Parking covered, and 75–100% Parking covered. Car passing events—any passenger car passing on the cyclist's left side—were observed in the recorded videos and coded. Additionally, pavement markings were coded as No Centerline, Dashed line (vehicle may cross over), and Solid line (vehicle may not cross over). These variables were coded along with the timestamp and trip information, which allowed for merging with the other data sources (e.g., GPS). The video data were also coded at 1Hz frequency.

3.3. Data Cleaning, Processing and Aggregation

Data collected from different sources were sampled at different frequencies. The first step of processing included changing the sampling rate of every data source to 1Hz. After down sampling to 1Hz, the GPS, physiological, lateral distance vehicle sensor, and video coded data were cleaned and merged into one comprehensive trip file by their timestamp. These trip files provide a robust picture of the roadway, traffic, and cyclist every second of the trip. The cleaned data were visualized using Tableau: a user-friendly tool that visually correlates physiological data with actual conditions encountered in the environment. Visualization helped identify participants with unusual behavior such as high EDA or HR values. Figure 3 shows a snapshot of the cyclist visualization tool with data from different sources of this naturalistic study.

3.4. Analysis

3.4.1. Dependent Variable – Skin conductance response and Skin conductance level—Electrodermal activity measured in real-time using Empatica E4 was analyzed to understand the cyclist's physiological stress levels during trips. Figure 4 highlights the different characteristics of an EDA signal. Measures such as response time, the slope of signal, amplitude, slope, and width of a skin conductance response are derived from these characteristics and used to identify points of physiological stress. Braithwaite et al., 2013 has discussed such characteristics and their observed values, indicating that any peak in EDA signal above 0.05μS is a skin conductance response, and it arises within 1–3s of the stimuli. Also, the strength of an event-related skin conductance response can vary between 2–3 μS and sometimes up to 8 μS. In a non-stimulus event, the frequency of peaks of skin conductance response ranges from 1–3 minutes.

As the first step of processing, the raw EDA data are filtered with an impulse response of order 32 and cutoff frequency of 0.4Hz to remove noise artifacts (Khalfa and Bertrand, 2016). This filtered EDA is smoother than the raw EDA containing essential information about the event-related responses. The next step was to break down the filtered EDA into phasic (SCR) and tonic (SCL) responses by segregating the trip data in short time intervals. The SCL or tonic response is the minimum value or baseline that gradually changes when the participant is stressed. The moving baseline allows controlling for various environmental stimuli that can impact the EDA (e.g., weather conditions, humidity, temperature, physical exertion, and wrist movement). The SCR or phasic response is the amplitude calculated above this baseline within the stress response interval of 3–5s after accounting for latency between stimulus and response (Braithwaite et al., 2013). Figure 5 shows raw EDA, filtered EDA, and the sample tonic (SCL) and phasic (SCR) EDA components calculated from it for a single trip.

One of the objectives of this paper is to understand the stress response elicited in cyclists during a car passing event which is identified repeatedly in literature as a factor for stress (Beck et al., 2019; Caviedes and Figliozzi, 2018; Gadsby et al., 2021). Hence, isolating these events and the respective EDA responses is important. The entire trip data for each trip was divided to represent two types of events – Car Passing and No Car Passing. Car Passing events comprise of a 7-second window where we expect the vehicle passing to have occurred in the first 2 seconds and record the peak amplitude of SCR in the next 5 seconds. Such responses are Event-Related – SCR (ER-SCR) representing a cross-level interaction between car passing events and EDA. The non-event-related SCR are 5-second aggregations where no car passing event was recorded.

The trip data are segregated in time order and coded as car passing and no car passing events. Later the data across the time window are aggregated and the peak amplitude SCR is extracted and mean SCL is calculated. During analysis, no car passing events are treated as the baseline condition versus car passing events in which the ER-SCR is studied. It is hypothesized that elevated SCR levels may be observed during car passing events versus the baseline of no car passing events. The final aggregated data are merged with trip purpose, comfort ratings, participant age, and gender from baseline questionnaires and trip diary entries completed after each trip.

3.4.2. Model for Analysis—A Linear Mixed-Effects Model(LMM) was chosen for analysis. Mixed models (Harrison et al., 2018) are generalized regression models with both fixed and random effects. Random effects represent a grouping variable such as trips completed by the same participant. Such models are particularly suitable for subjects with repeated measurements exposed to different scenarios in the traffic environment where categorical and continuous variables can be easily analyzed. Preliminary models were tested by segregating trips by time of day – Morning (6 AM – 12PM), Afternoon (12PM – 5 PM), Evening (5 PM – 9PM) and Night (9PM – 12AM). Such models did not produce significant results due to a high imbalance of data points across the different categories of the time studied.

The final model built included data points during daylight hours (6AM – 9PM). Additional filters were included to remove factors insignificant to the analysis. Night trips were excluded as the DRL was switched on throughout the night for all participants and hence it could produce biased results on the impact of DRL on cyclists' physiological stress levels. In terms of Surface Type, we reduced our dataset to street facilities and separate bike facility because those are locations where car passing events were possible. Different models were built using the forward selection technique where combinations of important variables representing the traffic environment (car passing events), roadway characteristics (pavement markings, surface type, parking type), and DRL were tested. Participant, trip, and interaction term of participant*trip were tested as random effects. Finally, the most parsimonious models, based on lowest AIC (Akaike's Information Criteria) and BIC (Bayesian Information Criteria) values were selected. Based on the probability from the t-test, the statistical significance of the effect is determined at a 95% confidence interval. Two models were built independently for SCR and SCL calculated as tonic and phasic EDA responses and were aggregated at the passing event level within the stress response interval of 5-seconds. The aim of building two models was to assess the short-term (phasic activations) and long-term (baseline EDA) impact of the different factors on the cyclist's physiological stress.

4. Results and Discussion

The final data filtered and compiled for analysis consisted of 209 trips of 37 participants. Table 1 shows a detailed summary of participants' demographic information and experience in biking. Participants were recruited evenly to both groups while maintaining the gender diversity. The recruited participants had an average of 7 years of riding the bike, yet did not feel completely comfortable riding on roads.

Table 2 shows the distribution of data for the independent and dependent variables of the model split across the car passing and no car passing events. It also lists the categories for each variable included in SCL and SCR models. The entire trip data was broken into two time windows according to these windows and aggregated. The categorical variables are listed with number of data points and the descriptive statistics across the time windows are presented for the continuous EDA variables in Table 2. The summary of aggregated data shows that most car passing events were recorded while riding along the shared street facility. During these time windows, very low parked vehicles were observed and no center line was often present.

Two separate models were built to assess the impact of external factors on Skin Conductance Response (SCR) and Skin Conductance Level (SCL). With each model, the factors are evaluated for influencing the SCR or SCL significantly. If the statistically significant effect is positive, the factor is identified to play a major role in increasing the cyclist's physiological stress. The final model results with fixed and random effect coefficients, p-value (for statistical significance) and confidence intervals are presented in Table 3 and Table 4.

For the categorical variables in the model, marginal effects are identified relative to a reference category (Surface Type Street, 0–25% Parked Vehicles, No Center Line, No Car Passed, No DRL use) set at the beginning of the model analysis. The SCR model represents the phasic activations in the EDA observed to external stimuli. The model results can be interpreted as factors associated with an increase or decrease in peak skin conductance response of the cyclist within the stress response window. SCR model results indicate an increase in peak skin conductance during car passing events compared to no car passing periods. For surface type, results were observed as expected, cyclist's peak skin conductance response decreases when riding on bike facility versus streets that are shared with other vehicles. Introducing or expanding separate bike paths has often been an essential administrative policy to encourage cycling and the success of this policy has been documented by several researchers who have studied cyclist's safety on the road (Lanzendorf and Busch-Geertsema, 2014; Pucher et al., 2010) However, while analyzing the effect of bike facilities on skin conductance level compared to street, the cyclist's stress level tends to increase. For the entire trip, the cyclists are often riding along different kinds of surface types switching between streets, bike facilities and sidewalks, which could cause the overall baseline stress level to increase. This could be a possible reason for the gradual increase in their skin conductance level in the long term.

In both the models it is observed that parked vehicles were associated with increases in the cyclist's SCR and SCL. However, the association was statistically significant only for SCR with 25–75% parked vehicles. Although the association between parked vehicles and cyclist stress has not been widely studied, it has been reported as a cause for discomfort to cyclists who are forced to travel on a narrow lane between parked cars on one side and continuous traffic flow (Caviedes and Figliozzi, 2018; Gadsby et al., 2021). In a quasi-naturalistic cycling study, 17% of the respondents reported parked vehicles as an important cause of stress after cycling in the streets of both Delft and Georgia (Gadsby et al., 2021). Hence, there is convergence between the stress-inducing factors calculated objectively in our study to factors reported subjectively by past researchers. With pavement markings, the hypothesis was that solid lines which indicate no crossing may cause the vehicles to drive close to the bike lane where the driver is still cautious to not cross the line. However, with dashed lines, drivers may maintain a safe distance as the cyclist can cross over at any point. The results obtained confirmed the hypothesis, and it was observed that the presence of dashed lines relative to no center line decreases the cyclist's SCR and SCL, while the presence of solid lines relative to no center line was associated with increased cyclist SCR and SCL. The effect of both solid and dashed pavement markings was statistically significant for SCR relative to no lines, whereas only the effect of dashed lines was significant for SCL.

The event related skin conductance responses studied were observed to increase with Car Passing Events. The impact of car passing events on cyclist's stress has been highlighted in other naturalistic studies (Caviedes and Figliozzi, 2018; Chaurand and Delhomme, 2013) such as the quasi-naturalistic study where 32% respondents reported it as a stressor (Gadsby et al., 2021). Often cyclists do not have a rear view of vehicles on the road; hence vehicles passing them can cause them stress as cyclists are surprised or develop a fear of being hit. Cyclists were requested to ride with DRLs one weekend to assess whether the lights may reduce their perceived risk and help them feel comfortable on roads. However, the model results show that DRL increased the cyclist's stress response with statistical significance in the SCL model indicating that the DRL had a negligible impact on the cyclist's stress. The variance around participants EDA recording across different trips is considered with the mixed-effects model. The statistical significance of the random effects' parameters shows variability in the stress response across different participants and for the same participants across different trips.

5. Conclusion

Cycling is recognized as a form of transportation that provides many benefits, including physical activity, low environmental impact, and reduction of vehicle traffic. However, the perceived risk and stress of cycling in traffic are significant barriers to realizing the benefits of bicycle use, particularly in cities where inadequate cycling infrastructure exists (Jacobsen et al., 2009).This paper attempts to understand the perceived risk as physiological stress and its underlying causes through a naturalistic study. The electrodermal activity recorded from Empatica E4 wrist-mounted devices are physiological stress biomarkers analyzed to identify stress-inducing factors in the traffic environment.

The naturalistic data collected were analyzed using two mixed-effects models. These models were built to study the peak skin conductance response (event/non-event related), the phasic activations observed in an EDA signal following an external stimulus, and the baseline skin conductance level. These variables represent the short-term and long-term impact on cyclist's physiological stress. The different factors studied include surface type, parked vehicles, pavement markings, car passing events, and DRL use. These models showed the magnitude and direction of the impact of different variables on the cyclist's physiological stress.

It was observed that riding on a separate bike facility was associated with less stressful cycling compared to shared streets. Parked vehicles were associated with increased stress levels. Pavement markings may affect cyclist stress because of the behavioral response they may elicit in passing vehicle drivers. With dashed lines, passing vehicle drivers may maintain a safe distance, allowing ample space for cyclists to ride, and their stress levels decrease. Solid lines prohibit crossing over, so drivers may choose to drive close to the marking but remain in the same lane as the cyclist, increasing the cyclist's stress levels. Car passing events were studied as an external stimulus that could elicit a high SCR in cyclists. True to the hypothesis, it was observed that car passing events were associated with increases in the cyclist stress levels in the form of event-related SCR within the 5-sec response window following the event.

While investigating the impact of DRL use, it was observed that riding with DRL was associated with increases in the cyclist's stress. A potential explanation could be that the study only includes participants with high levels of discomfort riding in traffic and riding with the DRLs may not have registered a substantial level reduction in their stress levels. This limitation can be overcome by studying the impact of DRLs on riders who are frequent and comfortable riding on roads who can be more sensitive to such small changes and show a significant influence on their stress levels. Although the DRL did not reduce cyclist stress levels, they may impact the behavior of passing vehicle drivers. As a future scope for this project, the authors will analyze the impact of DRL on the lateral distance between cyclists and passing vehicles.

Naturalistic and passive data collection has provided an excellent impetus for understanding road users' behavior, risk exposure, and comfort. This study allowed us to gather a comprehensive database combining multiple sources to accurately capture events on-road and the respective physiological response elicited in the cyclist. Studying EDA as a stress biomarker allows us to distinguish factors influencing the cyclist's perceived risk clearly, and the results were found to be converging with studies that approached it subjectively. Such a study design has allowed us to collect realistic data in a minimally disruptive method and conclude that parked vehicles, dashed pavement lines, and car passing events are significantly associated with increased stress among cyclists. These observations further apply pressure on the need for policies that eliminate cyclists' actual and perceived risks on the road. The research findings show the potential value for cities in investments that encourage cyclists by reducing stressful interactions in the roadway environment. This includes dedicated bicycle lanes, low-traffic routes and the avoidance of streets where cyclists must manage interactions with parked cars and traffic. Though these findings are somewhat intuitive, expanding such studies to other locations and demographics can help identify recommendations for improving cycling culture, for example among groups that are underrepresented among current urban cyclists. Thus, naturalistic studies are useful for evaluating cycling infrastructure and cyclist safety perceptions across cities and can inform approaches to increase bicycle ridership.

Acknowledgements and/or funding resources

The authors would like to thank Henna McCoy, Zosia Horak, Luke Sampson, and Laura Eckles for their assistance with data collection and Dr. Joe Cavanuagh for assistance with the analytical approach.

Funding:

This research was funded in part by grant #1R49CE002108-01 of the National Center for Injury Prevention and Control/CDC.

Data Statement

Due to the sensitive nature of the data collected in this study, participants were assured raw data would remain confidential and would not be shared.

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Highlights

- This study specifically targeted cyclists who expressed discomfort riding in traffic.
- Car passing events were observed to increase the cyclists’ stress.
- Parked vehicles and roads with dashed centerline markings increased cyclists’ stress.
- Daytime running lights had a negligible impact on cyclists’ stress on roads.
- Separate bike facilities were associated with less cyclist stress than shared streets.

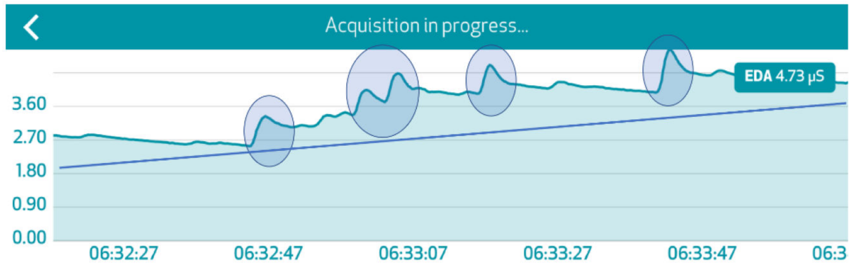

Figure 1.
Tonic and Phasic components of EDA signal (Empatica, 2015)

Figure 2.

Different Surface Types – [top - left to right] – Shared Roadway, Bike Facility, Sidewalk, Bike path not adjacent to a roadway, [bottom – left to right] – Gravel, other paved, other not paved

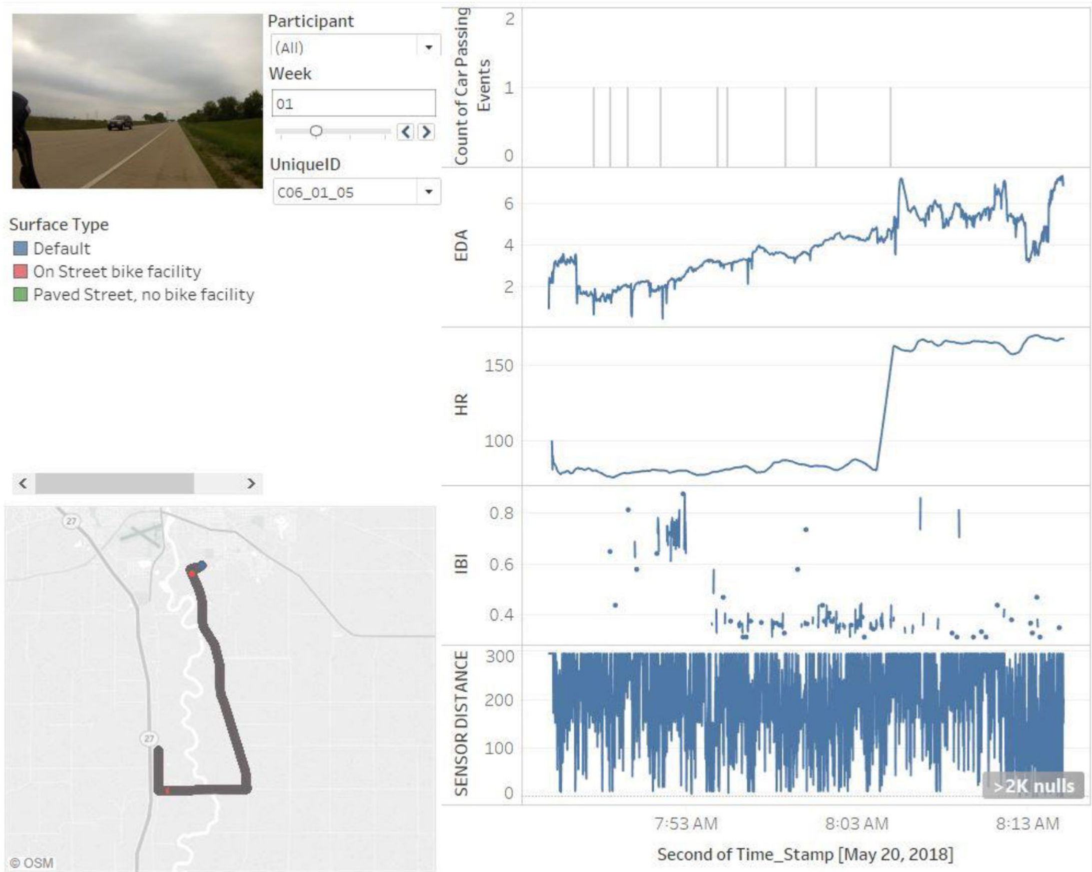

Figure 3.
Cyclist Visualization Tools showing a sample trip and its data from different sources

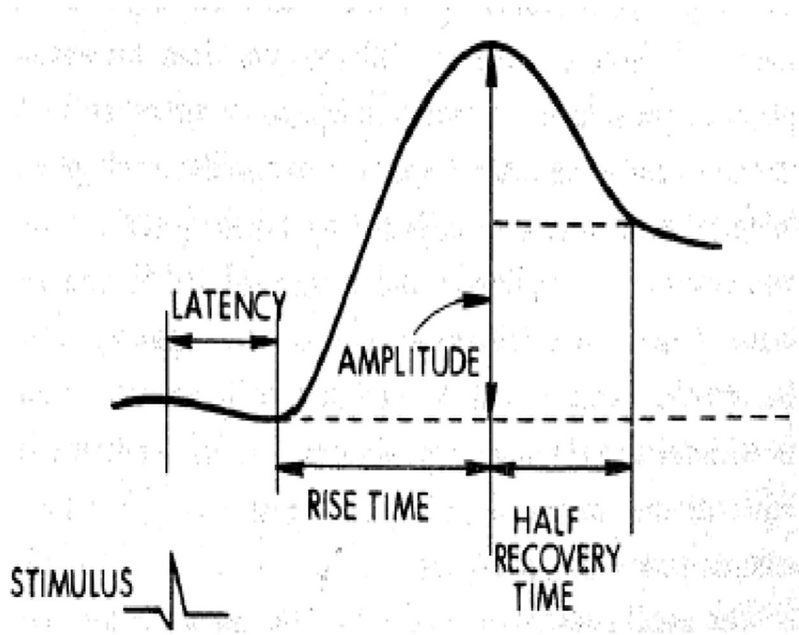

Figure 4.
Characteristics of an Event-related Skin Conductance Response (Dawson et al., 2000)

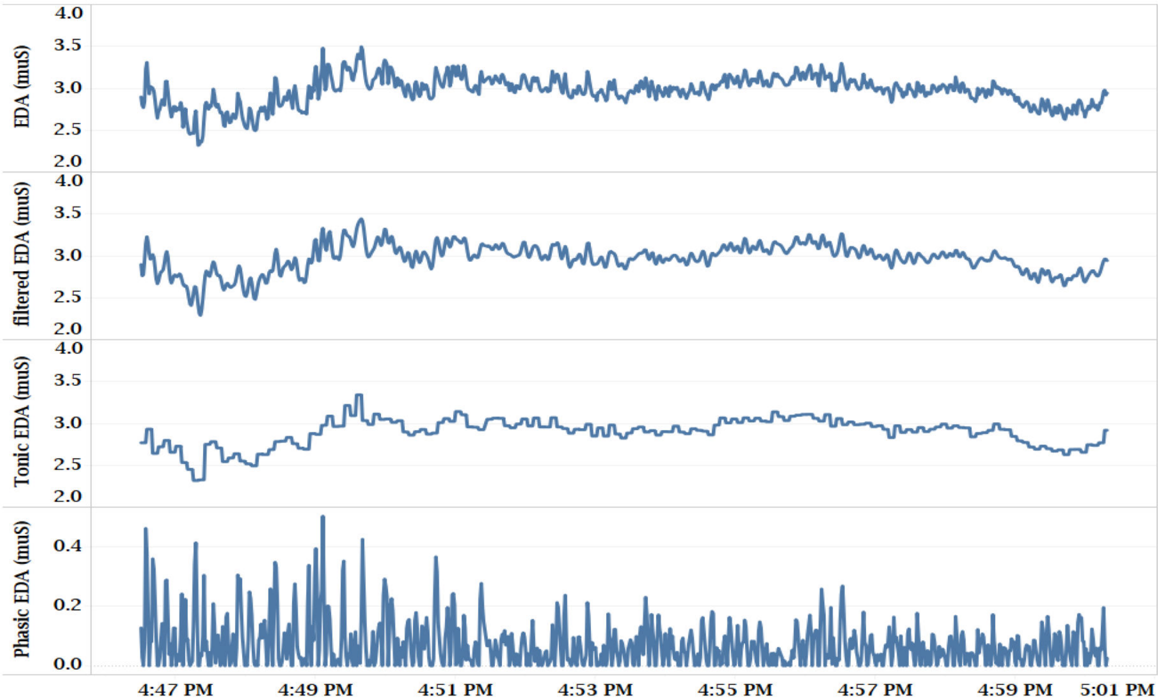

Figure 5.
Filtered EDA and its tonic and phasic components for a single trip

Table 1

Participant Summary

Participant Group	Intervention Group	Control Group
Participants	N = 20	N = 17
	Male = 10	Male = 10
	Female = 10	Female = 7
Age (years)	Range = 18–51	Range = 21–69
	Mean = 31.5	Mean = 39.06
	SD = 10.26	SD = 14.818
Biking Experience (years)	Range = 1–30	Range = 1–30
	Mean = 7.6	Mean = 7.412
	SD = 8.09	SD = 8.984
Comfort Rating	Range = 2–10	Range = 5–10
	Mean = 7.43	Mean = 8.28
	SD = 1.8	SD = 1.2
Trips Completed	With DRL = 58	Without DRL = 86
	Without DRL = 65	

Table 2

Data Summary by event

Variables	Car Passing Events (1256)	No Car Passing Events (20071)
Surface Type (data points)	Bike Facility(531) Street (725)	Bike Facility(4656) Street (15415)
Parking Type (data points)	0–25%(1155) 25–75% (54) 75–100% (47)	0–25%(17658) 25–75% (1171) 75–100% (1242)
Pavement Marking (data points)	Solid Line(429) Dashed Line(328) No Center Line(499)	Solid Line(4040) Dashed Line(9925) No Center Line(6106)
DRL use (data points)	DRL (326) No DRL (930)	DRL (4698) No DRL (15373)
SCR	Range = 0–8.05 μS Mean = 0.68 μS SD = 1.06 μS	Range = 0–19.15 μS Mean = 0.63 μS SD = 1.04 μS
SCL	Range = 0–104.41 μS Mean = 14.81 μS SD = 21.36 μS	Range = 0–128.5 μS Mean = 12.68 μS SD = 19.22 μS

Table 3

SCR Mixed Effects Model Results

Fit Statistics				
AICc	53768.804			
BIC	53856.437			
Random Effects	**Coefficient**	**P-value**	**95% Lower**	**95% Upper**
Participant*Trip ID	0.372	<.0001**	0.296	0.448
Fixed Effects				
Intercept	0.557	<.0001**	0.458	0.658
Surface Type[Bike Facility]	−0.03	<.005**	−0.049	−0.012
Parking Type[75–100% Parking]	0.017	0.40	−0.022	0.056
Parking Type[25–75% Parking]	0.046	<0.05**	0.009	0.084
Pavement Marking [Dashed Line]	−0.052	<.0001**	−0.074	−0.030
Pavement Marking [Solid Line]	0.045	<.0001**	0.026	0.063
Car Passing Event[Car Passed]	0.026	<.05**	0.001	0.051
DRL use[DRL]	0.079	0.15	−0.026	0.164

Referent groups: Street, 0–25% Parked Vehicles, No Center Line, No Car Passed, No DRL use

Table 4

SCL Mixed Effects Model Results

Fit Statistics				
AICc	161036.52			
BIC	161132.1			
Random Effects	**Coefficient**	**P-value**	**95% Lower**	**95% Upper**
Participant*Trip ID	140.408	<.0001**	113.077	167.738
Fixed Effects				
Intercept	8.2999	<.0001**	6.435	10.164
Surface Type[Bike Facility]	0.538	<.0001**	0.302	0.774
Parking Type[75–100% Parking]	0.466	0.06	−0.022	0.954
Parking Type[25–75% Parking]	0.274	0.25	−0.194	0.742
Pavement Marking [Dashed Line]	−1.533	<.0001**	−1.808	−1.259
Pavement Marking [Solid Line]	0.209	0.07	−0.022	0.440
Car Passing Event[Car Passed]	0.019	0.90	−0.296	0.318
DRL use[DRL]	2.118	<.05**	0.293	3.943

Referent groups: Street, 0–25% Parked Vehicles, No Center Line, No Car Passed, No DRL use