Exploring Variability in Cyclists Riding Posture through Naturalistic Data: A Computer Vision and Bayesian Modelling Approach

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INTRODUCTION

Vulnerable Road Users (VRUs) are frequently involved in road traffic accidents, accounting for more than half of all road traffic deaths (WHO, 2023). Among these VRUs, cyclists, who are exposed to a high risk of injuries (Cittadini et al., 2024; Stigson et al., 2020), form a significant portion. The severity and type of injuries sustained by cyclists can be influenced by various factors, including riding posture, helmet usage, bike type, and speed.

Previous research, such as the study conducted by (Leo et al., 2023), has explored the posture and riding preferences of VRUs (specifically e-scooter riders) in a controlled field experiment. Controlled experiments, while valuable, have their limitations. To overcome these limitations, this study utilizes naturalistic data, which offers insights into rider behaviors and postures under real-world conditions. Video data collected from cyclists in a naturalistic setting combined with computer vision algorithms can provide information not only about their posture but also about their sex and helmet usage. By understanding and modeling the posture of cyclists, we can leverage tools such as human body models and simulations to recreate various crash scenarios. The recreated crashes allow us to gain a deeper understanding of injury mechanisms, ultimately contributing to decreasing cyclists' injuries.

METHOD

The data for this study was collected in Gothenburg, using an instrumented e-scooter and bicycle, each equipped with a camera that recorded videos of surrounding road users (see figure 1A). The collection process was carried out at various locations across the city, with a particular focus on high-density cycling routes. The data collection was scheduled during peak hours, specifically at 8 AM and 4 PM, over a span of two weeks in April 2024.

Unique bicyclist frames were extracted using YOLOv7 (Wang et al., 2023) in combination with the Simple Online and Realtime Tracking (SORT) framework (Bewley et al., 2016). The computer vision approach assigned a unique ID to each cyclist in the video, and a frame was subsequently extracted for each cyclist when the rider was closest to the center of the frame. The presence of pedestrians and other road users in the frame could result in unnecessary detections during the posture estimation process, which would subsequently require filtering. To avoid this additional filtering process, a black mask was added in the area outside the bounding box of the cyclist. The posture of the cyclist was estimated using the YOLOv8 Pose estimation algorithm (Jocher et al., 2024). The algorithm enabled the detection of 17 key points of the cyclist, as shown in Figure 1B. The estimated key points correspond to anatomical structures such as the nose, eyes, ears, shoulders, elbows, wrists, hips, knees, and ankles. Using the key points, the arm angle and the torso angle were estimated. The arm angle was computed as the angle between the line joining the shoulder and the wrist with the vertical axis. Similarly, the torso angle was computed as the angle between the line joining the shoulder and the hip with the vertical. Outliers in the arm and torso angles were determined based on the maximum or minimum angle achievable by human anatomy. The key points estimated on a cyclist, along with the computed arm and torso angles, are illustrated in Figure 1B. The extracted frames were manually annotated with respect to three key aspects: helmet usage, sex, and bike type. To avoid any influence of personal bias, two annotators labelled the frames. Helmet usage was annotated in a binary fashion, distinguishing between *helmet used* and *helmet not used*. Sex was labelled as either *male* or *female*. The type of bike was categorized into *classic*, *hybrid*, or *race*. Further classification included either *e-bike*, if the bike was an assisted bike, or *traditional* bike.

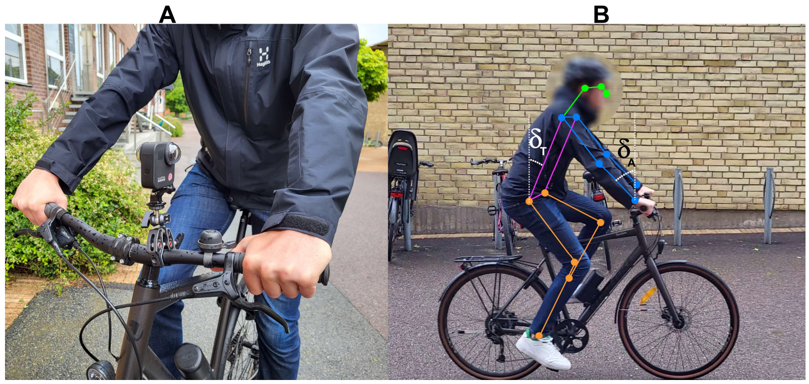

Figure 1. Panel A: Camera mounted on bike, Panel B: estimated posture and angles

Using the pre-processed data, an initial descriptive statistical analysis was conducted to understand the characteristics of cyclists' variability. To determine the relationships between sex, helmet usage, and bike type, a Chi-squared test of independence was performed (R Core Team, 2023). Subsequently, three Bayesian regression models (Bürkner, 2017) were developed to explore the associations between the predictors (sex, helmet usage, and bike type) and the dependent variables (arm and torso angles). The first regression was modelled with sex, helmet usage, and bike type as predictors. The second model was built with sex and helmet usage as predictors, while the third model used sex and bike type as predictors.

RESULTS

In this study, data from 240 unique cyclists was used for analysis and modelling. The result of the descriptive statistical analysis indicates the distribution of cyclists' sex was 62.3% male and 37.7% female. Helmet usage was observed in 74.5% of the cyclists. Regarding the bike type, 43.9% were classical city bikes, 45.6% were hybrid bikes, 10.5% were race bikes. E-bike accounted for 30.4%. The Chi-squared test results revealed the independence between sex and helmet usage, while bike type was found to be dependent on sex and helmet usage.

Among the Bayesian regression models, the model using sex and bike type as predictors produced the smallest residual errors. Equation 1 represents the Bayesian regression model for both the arm and torso angle. Due to the absence of prior knowledge of the predictors, flat priors were used in the model. The coefficients b_{sex} and b_{bike_type} followed a normal distribution N(0,10), the intercept b_0 followed N(0,40), and the residual standard deviation (sig) followed a Cauchy distribution (0,5). The baseline for the model is "Male riding classic bike", with b_0 representing the angle for that configuration. The posterior predictive distributions for arm and torso angle are shown in Figure A1 in Appendix A.

$$angle \sim b_0 + b_{sex} \cdot x_{sex} + b_{bike_{type}} \cdot x_{bike_{type}} + b_{ebike} \cdot x_{ebike} + b_{interaction} \cdot x_{bike_{type}} * x_{sex} + sig \quad (1)$$

The model shows that being female results in lower torso angles and a higher arm angle when compared to the baseline in hybrid or racing configuration. E-bike riders have more upright positions compared to those on classic bicycles. Data, code and figures are available at https://github.com/chiaraf10/strc2024_cyclists_riding_posture_variability.

CONCLUSIONS

In this study, we developed Bayesian regression models to estimate the posture and explore the variability of cyclists using naturalistic data collected and processed with computer vision algorithms. The data indicates that 74% of cyclists wore helmets and around two-thirds were male, with no observed dependency between helmet usage and sex. The developed models can facilitate in-crash simulations to assess the injury risk of cyclists by providing inputs on cyclist positioning. While adding more anthropometric parameters such as arm length could enhance the model, obtaining such data from images would require additional processing and verification, which is planned for future work.

ACKNOWLEDGEMENTS

The image data were collected within the Drive Sweden project "MicroVision: Development, Testing, and Demonstration of a Real-Time Support System for Electric Vehicle Riders" (2023-01047), upon approval by the Swedish Ethical Review Authority (Etikprövningsmyndigheten; Ref. 2024-00329-01). We thank Jonas Bärgman and Jordanka Kovaceva for providing feedback on the draft.

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APPENDIX A

The posterior predictive distributions for arm and torso angle are shown in Figure A1 below.

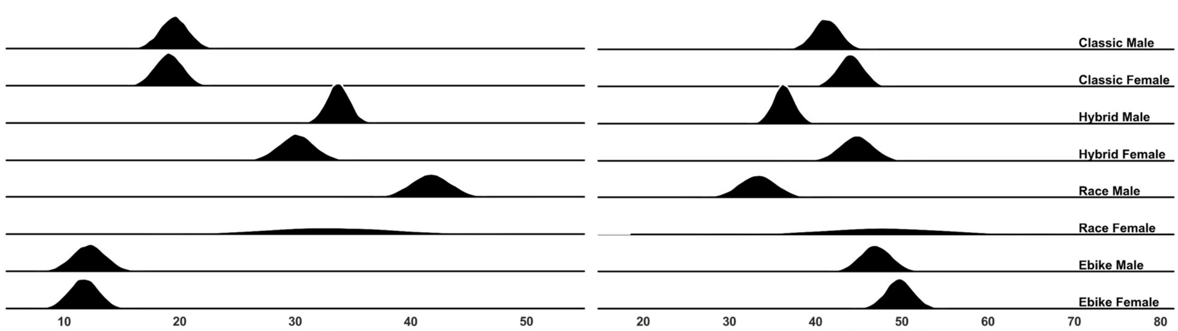

Figure A1: Posterior predictive distributions of arm and torso Bayesian model