When the E-bike Takes Over: Speed Precision and Perception of Cruise Control for Cyclists

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ABSTRACT

E-bikes are recognized for their sustainable transportation benefits. However, the higher speeds associated with e-bikes pose an increased risk of potential accidents and hinder fluid riding in swarms with conventional bicycles. In this paper, we analyze the accuracy of maintaining an unknown speed, assess the associated workload, and investigate the self-reported speeds of e-bike cyclists in order to adapt the electric assistance to dynamic speed limits based on the surrounding traffic conditions. Our results from a pilot study with 15 participants show that the accuracy of maintaining a speed limit through active motor control and the associated workload are influenced by factors such as the level of electrical assistance and the perception of motor disengagement. E-bike cyclists using higher levels of electrical assistance demonstrated more accurate target speed maintenance. On average, participants consistently underestimated adapted speed limits, which were also influenced by the level of electrical support.

CCS CONCEPTS

• **Hardware**; • **Human-centered computing** → Ubiquitous and mobile computing systems and tools;

KEYWORDS

Connected Bicycles, V2X, E-Bikes, Smart Mobility, E-Mobility, Cycling, Speed Perception, Cruise Control

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1 INTRODUCTION

Bicycles and electric-assisted bicycles (e-bikes) are often considered one of the most sustainable modes of transportation. Their minimal environmental footprint [38], promotion of health through involved physical activity [10], and efficient use of road space [24, 53], along with reduced infrastructure maintenance costs [27], collectively position bicycles and e-bikes at the forefront of sustainable transportation alternatives [64]. A significant number of short car trips could be replaced by walking or cycling, reducing CO_2 emissions from car travel by about 5 % [58].

Currently, governments worldwide are investing in new bicycle infrastructure for improved cycling comfort and safety [11, 31, 40]. However, research suggests a nuanced perspective, as early studies from 2013 argue that transitioning to bicycle commuting may not necessarily lead to a reduction in fatalities and could potentially result in an increase in the incidence of serious road injuries [67]. Between 2021 and 2022, the incidence of injuries related to micromobility vehicles and e-bikes surged by 21%. Additionally, since 2017, the frequency of these injuries has shown an average annual increase of 23% in the United States [16]. German statistics bring attention to a rise in fatal accidents involving e-bikes, a trend linked to their higher speeds compared to conventional bicycles [20]. The active promotion of bicycle helmets can counteract fatal accidents by an increased prevalence of helmet usage among cyclists, as demonstrated in Denmark's traffic [62]. Recent European crash statistics reveal a diminished occurrence of severe head injuries among e-bike cyclists, a trend that may be linked to their increased and widespread use of helmets [59]. Additionally, statistics from the United States also indicate a greater likelihood of helmet usage among e-bike cyclists. Nevertheless, the data on injury patterns and hospital admission rates indicate that e-bikes are associated with a higher level of injury severity compared to conventional bicycles [21, 84]. It has been found that e-bike cyclists regularly travel at higher speeds, thereby posing an elevated risk of serious accidents [68]. To mitigate the safety concerns posed by high-speed e-bikes, the Amsterdam government is currently deliberating measures such as imposing a speed limit of 20km/h for e-bikes or relocating them to car lanes [75, 76].

To further enhance cyclist safety and riding experience, there is a growing interest in research and industry to connect cyclists with the surrounding traffic and infrastructure [3, 61]. The core concept revolves around the sharing of position and speed measurements through the cyclist's smartphone, or via external cameras in the environment. The cyclist's phone or another smart cycling solution, such as augmented helmets [51, 80, 82], or haptic feedback on the handlebars [60], subsequently alerts cyclists to potential collisions or provide riding recommendations. For example, it is estimated that e-bike battery consumption can be significantly reduced by recommending speeds on smartphones to avoid energy-intensive start-and-stop scenarios at traffic lights [73]. By 2027, it's expected that all new smartphones will be equipped with vehicle-to-everything (V2X) communication capabilities for improved road safety [5].

This paper investigates the impact of dynamic motor control on e-bike cyclists, a technology similar to cruise control (CC) for vehicles like cars and trucks. Within the cycling domain, CC has the potential to optimize the overall traffic flow through dynamic adjustments of the assisted speed, e.g., in accordance with traffic light phases using V2X communication. Since CC eliminates the need for cyclists to constantly monitor their speed and can provide incentives for slower speeds [4], it has the potential to enhance traffic safety. However, to the best of our knowledge, it has been unclear how cyclists perceive and adapt their speeds to such a technology. In our pilot study with 15 participants, we show that cyclists can accurately maintain different unknown adjusted speed limits using CC while simultaneously underestimating the self-reported speed. Our findings reveal that e-bike motor power influences speed perceptions. Moreover, we provide insights into the workload associated with cycling while using adaptive electrical support and give an outlook and implications on future research in the area of swarm cycling.

2 RELATED WORK

Over the past decades, researchers have dedicated significant efforts to advancing mobility safety. This focus has recently led to a growing interest in understanding and addressing the safety concerns and user experiences of vulnerable road users [30, 41, 49]. For example, the quality of a road surface has been found to influence not only ride comfort [8, 23], but also safety [42] and cycling speeds [14].

There is a current research interest in integrating driver assistance functions and levels of automation that were developed for cars and trucks into bicycles [47, 50]. For instance, *Cruise Control*, originally invented by Teetor in the mid-1940s, allows vehicles to automatically maintain a constant speed [70]. *Adaptive Cruise Control* (ACC) enhances this technology by also ensuring a safe following distance from the vehicle ahead [87]. Cooperative ACC refers to a *Platoon* or convoy of vehicles, often autonomous or semi-autonomous, that travel closely together in a coordinated manner to improve fuel efficiency, traffic flow, and overall transportation system effectiveness [77]. Forming bicycle platoons [12] or swarms [54] is envisioned to optimize visibility in traffic, promote a feeling of being together [66] and optimize traffic flow [86]. These systems utilize haptic, acoustic, or visual cues to synchronize cycling speeds within a group. However, feedback methods, such as vibrations on the handlebars [60] or augmented vision [50, 81] might be utilized for warnings or turn indications in the future. Active motor control holds the potential to reduce cognitive workload in maintaining a desired speed, but, to the best of our knowledge, there has not been a systematic assessment of how accurately cyclists can maintain a specific speed using this approach [22]. Optimized traffic signal control could leverage adjusted e-bike speed limits to enhance overall traffic flow [46] and reduce battery power consumption [73]. Although design guidelines for speed control and involved user experience have been investigated [4], accuracy of maintaining different speeds, e-bike power modes and involved workload were not investigated.

The potential beyond recreational cycling has sparked ideas of assisted exercising [6]. When cycling over the pleasant pedaling rate of about 60 revolutions per minute (rpm), physiological effects become noticeable [15]. By controlling the transmission of a bicycle, e.g. pedaling frequency [19] and pedaling resistance [1, 55], the heart rate [17] and maximum speed can be influenced. To strategically control cyclists' speeds, research found that imprecise split-time feedback does not significantly impact racing cyclists [85], whereas competing against a more powerful trial can result in improved performances [72]. Manipulating a clock has been shown to enhance time to exhaustion on a cycle ergometer [57]. Results on altering pedestrian walking speed by augmented acoustic footstep feedback [69] inspired researchers to investigate similar effects on bicycles [52]. Also in virtual reality, researchers are investigating speed deception [45].

Perceiving speed accurately while cycling can be challenging, as cyclists tend to underestimate their speeds, potentially contributing to increased risks of injuries [74]. Moreover, self-reported and the external-rated road behavior greatly differs between cyclists and other road users [78]. Interestingly, the use of safety reflective vests by cyclists has been associated with an overestimation of their speeds by other road users [71].

To summarize, the existing body of related work shows a multifaceted exploration into mobility safety, technology integration, and the broader aspects of cycling, including speed control, health implications, and the perception as well as user experiences of cyclists in various contexts. There is a lack of systematic assessments regarding the accuracy and workload of cyclists in maintaining desired speeds through active motor control using different levels of motor support. Additionally, it is unclear how accurately cyclists can estimate their speed while being controlled by the e-bike system. These parameters are crucial for a seamless integration of CC applications into daily traffic. For example, traffic light systems require cyclists' speed fluctuations to provide accurate instructions [4], while automated swarm formation depends on speed accuracy for effective coordination and cooperation among cyclists [12]. Both potential CC applications require that cyclists remain constantly aware of the surrounding traffic and be conscious of whether they are going too fast or too slow.

3 PROTOTYPE

To address the gap in maintaining a desired speed through active motor control, we developed a prototype that allows the electrical assistance to be turned off in relation to a target speed limit. Our technology is similar to established tuning and motor chipping/hot-rodding methods, though it comes with the necessary constraint of not enabling the bypassing of speed limits. Hence, our e-bike is compliant with German traffic regulations, specifically §63a(2) of StVZO, ensuring its secure operation in regular traffic while providing dynamic motor assistance up to 25 km/h. To ensure traffic regulation compliance, e-bikes typically measure speed using a magnet attached to the wheel spoke. As the magnet passes a sensor mounted on the frame, the current speed is computed using the known wheel circumference and the time elapsed since the last trigger. Once the e-bike reaches the speed limit, the motor turns off. Similarly, adding a magnet on the pedal allows for the measurement of cadence in rpm by tracking the time of each rotation.

Our prototype, shown in Figure 1 on the right, utilizes this principle for motor assistance control. An Arduino with Bluetooth Low Energy (BLE) monitors the current speed and cadence, and it records these measurements, along with the motor assistance state (on or off), adjusted speed limit and current geographic position as well as timestamp, onto an SD memory card. Upon reaching the desired speed limit, our prototype injects additional triggers into the e-bike's embedded speed control unit, simulating cycling above the speed limit. Consequently, the e-bike motor can be deactivated according to a modified speed limit. Trigger injection refers to the insertion of an electrical signal into the sensor data wire, simulating the effect of a magnet passing by the sensor. To manually adjust the speed limit, we developed an experimental BLE application for Android. To rebuild our prototype, we have provided a detailed description, including a tutorial, example schematics, and Arduino code, on our GitHub [1].

We integrated our prototype onto a size M and L *HNF Nicolai UD4 All-Terrain* 27.5" e-bike utilizing the *4th Generation Bosch Smart System Performance Line CX* motor, as used in [41] for cycling experience assessment, equipped with a maximum torque of 85 Nm. The e-bikes provide different assistance modes to control the torque. For example "Eco" mode optimizes energy usage for an extended range of up to 100 km on a fully charged battery, emphasizing energy efficiency at the cost of motor power. In contrast "Turbo" mode delivers maximum motor power, at the cost of increased energy consumption, limiting the cycling distance to 60 km. According to the manufacturer Bosch, the manual pedal force is increased by 60% in Eco mode and up to 340% in Turbo mode [2].

4 STUDY

Our primary goal was to assess how accurate cyclists maintain a target speed limit through active motor control. The independent variable of motor power was added to better estimate how cyclists would adapt to other e-bike systems. Secondarily, the objective was to evaluate the self-perception of cycling speed and associated workload among e-bike cyclists using CC. To eliminate any confounding variables related to visual speed and motor power feedback, the display on the e-bike was removed, and all LEDs indicating motor support power levels were covered.

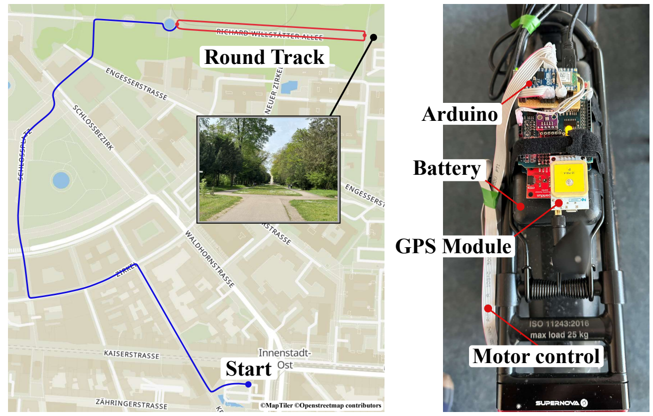

Figure 1: Study route (left) and prototype (right). On the blue track we set the motor assistance to 25km/h. On the round red track we varied the assistance limit from 16 to 22 km/h. The prototype is powered by an external battery and additional sensors and magnets were mounted on the frame, rear wheel and pedals to measure speed and cadence.

4.1 Participants

We invited 15 participants (13 male, 2 female) aged from 23 to 40 years ($M = 27.7 years, SD = 4.7 years$). Participants were recruited through university mailing lists and WhatsApp groups. Studies were only conducted during daytime. On average, the participants had a height of 1.80 meters ($SD = 0.11m$) and a weight of 80 kilograms ($SD = 18.5kg$). We gathered height and weight data for a better reproducibility of our study due to potential impacts on e-bike acceleration patterns, with height being a factor affecting wind resistance. Seven of our participants were familiar with cycling on e-bikes, the other eight participants have never used an e-bike before or tried it only once. All participants used conventional bicycles in their daily mobility and reported an average cycling speed of 17.9km/h. The participants who were familiar with cycling on e-bikes agreed on a five-point scale ($M = 4.25, SD = 0.66$) to feel safe when riding an e-bike.

4.2 Study Design

The study took place near the city center of Karlsruhe, Germany in a nearby park on a circular track, as illustrated in Figure 1 (left), on flat terrain. We initially handed out an introduction questionnaire in our lab, covering general questions about participants' bicycle usage, their experience with e-bikes, and encountered traffic situations. After a brief introduction to e-bike usage and putting on safety equipment, participants were taken outside the building to test the e-bike and its behavior in a courtyard. As we had two bikes of different sizes (M and L), participants were assigned the bike that best matched their height.

Once participants were familiar with the e-bike, we instructed them to maintain the maximum electrically assisted speed and then estimate their speed. They were able to freely adjust the gearshift throughout the experiment and were reminded to pay attention to the surrounding traffic. The experimenter set the participant's e-bike either in *Eco* mode or in *Turbo* mode in a counterbalanced order for each participant, with a speed limit of 25 km/h. On the

1 https://github.com/M-Schrapel/E-bike-Cruise-Control
2 https://www.bosch-ebike.com/en/help-center/performance-line-sx-for-the-smart-system/asset-asf-01045

way to the park, the experimenter cycled in front of the participant with his e-bike in Turbo mode, aiming to manually maintain a speed over the limit at around 30 km/h. Because participants were instructed to maintain the maximum supported speed, the experimenter riding ahead was able to monitor the preceding traffic, guide the participant to the round track, and avoid the effects of synchronized speeds resulting from riding side-by-side. The blue route, as illustrated in Figure 1, encompassed straight bicycle roads with low traffic. The experimenter waited at each intersection until the participant arrived before continuing the ride. After arriving at the round track, marked in red, the experimenter inquired about the maximum assisted speed perceived by the participants and assessed their workload using the NASA-Task Load Index (TLX) questionnaire [28]. Additionally, we requested participants to describe the e-bike riding behavior using a single word, with a list of illustrative examples provided: dynamic, lively, quiet, rough, sporty, elegant, comfortable, strenuous, stressful. Furthermore, we surveyed the participants whether they noticed when the motor assistance turned off and whether they actively counteracted motor disengagements, using a 5-point scale.

At the round track, the experimenter adjusted the speed limit to 16, 19, or 22 km/h using our experimental BLE app and configured the motor support either in Eco or Turbo mode in a counterbalanced order for each participant. We selected the speeds based on related works and within a common range of cyclist speeds. A speed of 16 km/h corresponds to the median speed of cyclists on shared paths [9] and 19 km/h to the average speed of e-bike cyclists in urban areas [68]. In [4], a static speed limit of 22 km/h was used to investigate how cyclists experience cooperation with traffic lights and modified e-bikes, providing us with a broad range of reasonable speeds for cyclists in daily traffic. The motor modes Eco and Turbo correspond to the minimal and maximal electrical support provided by the selected e-bikes. In addition, we included a mode of no support *None* to assess the participants' behavior without any electrical motor assistance. This baseline condition is valuable for understanding how participants adapt their cycling strategy when devoid of electrical support and provides insights into their reliance on motor assistance at different power levels. Our within-subject study design required all participants to perform each combination of motor support mode and target speed in counterbalanced order to eliminate potential learning effects. In None mode without electrical assistance, we decided not to provide further instructions for measuring the preferred cycling speed, as mentioning target speeds could potentially bias cyclists in their subsequent self-reported speeds. Participants were instructed to cycle half of the round track, resulting in a route length of 300 meters for each trial and a total length of 2.1km for the included 7 trials. The experimenter followed the participant in a short distance and watched the traffic all the time. After each trial, the experimenter reiterated the previous mentioned questions, including the NASA-TLX questionnaire, and documented participants' comments. In case of any unforeseen traffic circumstances, such as a participant having to brake, the trial was repeated immediately afterward. On the return journey to the lab, the experimenter again configured the participant's e-bike in either Eco mode or Turbo mode, in a counterbalanced order, with a speed limit of 25 km/h. The experimenter cycled in front of the participant again and then repeated the questionnaire one last time. Back in the lab, the experimenter handed out a final questionnaire to assess participants' affinity for technology interaction (ATI) [25], the System Usability Scale (SUS) [34], and general questions attached in the Appendix together with a free-text field for any additional comments. The SUS was only assessed once to avoid overloading the participants with questions after each trial. The study lasted approximately 90 minutes and involved a total cycling distance of 4.5 km. Participants were provided with a bar of chocolate, a bottle of water, a coffee, and 15 Euros as compensation for their participation.

5 RESULTS

From our questionnaire we obtained an average ATI score of $M = 3.87$ ($SD = 0.81$, *Cronbach's alpha* $= 0.89$), indicating a medium affinity for technology interaction among our participants. The average SUS score ($M = 73.33, SD = 12.88$) suggests a good usability in maintaining a target speed with our adapted motor assistance without speed feedback.

5.1 Data Analysis

To analyze our recorded data, we initially excluded acceleration and braking phases from the samples. These phases could have potentially affected the analysis of how accurately cyclists maintain specific target speeds. Subsequently, we evaluated the normality of dependent variables for each factor level using the Shapiro-Wilk test and assessed homogeneity of variance using Levene's test. For the analysis of the two independent variables (motor mode and target speed), we applied an aligned rank transformation (ART) to the data to perform a nonparametric two-way repeated measures ANOVA when ANOVA assumptions were violated. This was followed by pairwise post-hoc tests on the transformed data with Holm correction. In cases where only one independent variable, e.g. motor mode, was considered, we selected Friedman's test followed by a Nemenyi post-hoc test. A significance level ($\alpha = .05$) was chosen for all statistical tests. The data were prepared using Python 3 and analyzed in R [65] using the packages ARTool [36], emmeans [44], dplyr [83], pwr [13], and stats. Our dataset is available on our GitHub [3].

5.2 Measured Speeds

Figure 2A shows the measured speeds, where "None" represents the trials in the absence of motor assistance, E stands for the "Eco" mode, and T for "Turbo" mode with the accompanying number indicating the target speed limit. Figure 2B illustrates the measured cycling speeds normalized to specific target speeds, depending on the motor mode.

In order to test for significant differences in the measured speeds across the independent variables (target speed and motor mode), samples from the None mode were excluded since measurements were not taken at different target speeds. The non-parametric ANOVA type II results indicated significant effects of motor mode ($F(1, 56618) = 62.073$), Speed Limit ($F(3, 56618) = 54522.132$, $p < .001$), and their interaction ($F(3, 56618) = 502.490$, $p < .001$) on measured speed. The post-hoc analysis identified significant differences between each pair of target speeds ($p < .001$) and between

[3] https://github.com/M-Schrapel/E-bike-Cruise-Control

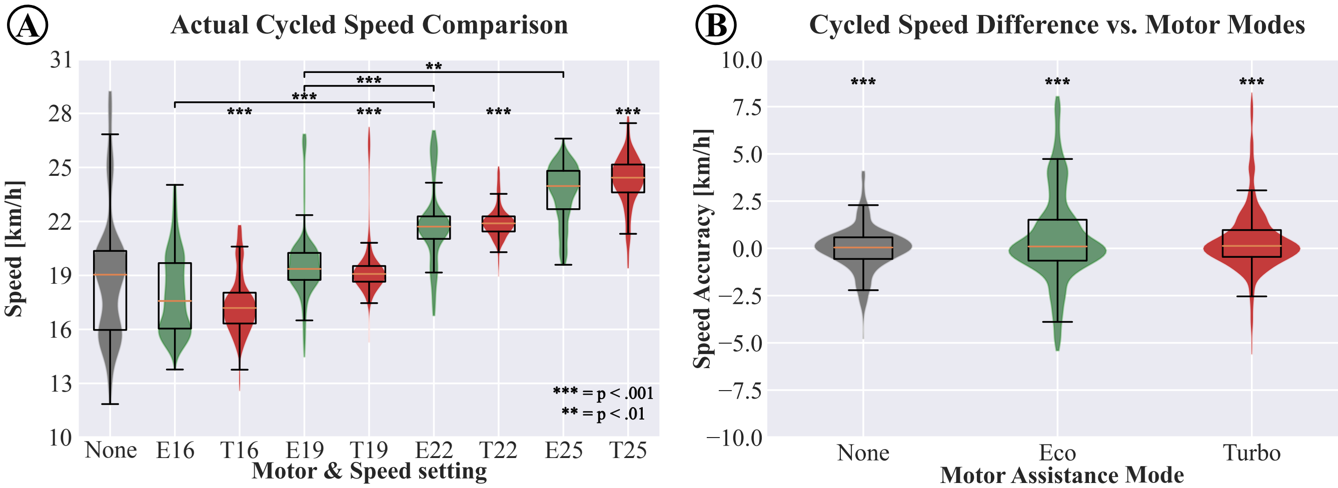

Figure 2: Actual cycled speed comparison. A shows the cycled speeds in each trial and B the normalized cycled speed distribution for each motor mode. The violin plots marked with asterisks but without lines show significant differences to all possible combinations.

both motor modes ($p < .001$). To further explore the significant interaction, pairwise comparisons were conducted. The results revealed significant differences between most pairs, except for E16 vs. E19 ($p = .173$), E16 vs. E25 ($p = .068$), and E22 vs. E25 ($p = .070$). A power analysis was conducted to ensure that the study had at least an 80% chance of correctly identifying true effects. The sample size per motor mode ($N = 28230$) was sufficient to detect the small effect ($f = 0.035$), which required $n = 3253$ samples per group. Similarly, for target speed ($f = 0.985$, $n = 4$ samples per group) and the interaction between motor mode and target speed ($f = 0.169$, $n = 64$ samples per group), the study was adequately powered. To justify the small effect of motor more, the average cycled speed in Eco mode over all collected raw measurements ($M = 18.52km/h, SD = 4.14km/h$) is close to the average speed in Turbo mode ($M = 18.92km/h, SD = 3.95km/h$). Especially at lower target speeds, we observe distinct speed fluctuation patterns, as illustrated in Figure 2A.

For the analysis including the None mode, all samples from the Turbo and Eco modes were normalized by subtracting the target speed. In None mode, the corresponding average cycled speed was subtracted from each participant's samples. This approach enabled us to capture and compare the fluctuations around all target speeds in relation to the individual preferred speeds, as shown in Figure 2B. A Friedman's test indicated significant differences between the motor modes ($Q(2) = 200.69, p < .001$). The Kendall's W value of $W = 0.406$ suggests that there is a moderate effect in how the motor modes affect the cycled speed. A subsequent post-hoc test showed that all modes differ from each other ($p < .001$). Therefore, a significant difference was observed in maintaining a speed around a desired target speed among the three motor support modes: Turbo ($M = 0.29km/h, SD = 1.69km/h$), Eco ($M = 0.26km/h, SD = 2.31km/h$), and None ($M = 0.0km/h, SD = 1.15km/h$). In None mode, the preferred average cycling speed ($M = 18.95km/h, SD = 3.49km/h$) ranged from $15.43km/h$ to $27.28km/h$.

To get further insights into the relation with preferred speeds in the None mode, we analyzed the cadence among the different motor modes. We performed a Friedman's test that indicated a significant difference among the three motor modes ($Q(2) = 492.63, p < .001$). The Kendall's W value of $W = 0.729$ suggest that there is a strong effect in how the motor modes affect the pedaling frequency. The post-hoc test showed that the cadence significantly differs between Turbo mode and Eco mode as well as Turbo mode and None mode ($p < .001$). However, no significant difference was observed between None and Eco mode ($p = .35$). Although Turbo and Eco mode exhibited a significant difference, the overall averages for Turbo mode ($M = 58.58rpm, SD = 13.76rpm$), Eco mode ($M = 63.21rpm, SD = 13.8rpm$), and None mode ($M = 62.78rpm, SD = 17.17rpm$) were in a comparable range with minimal physiological demand [2, 15].

5.3 Self-reported Speeds

We followed the methodology outlined in 5.2 for analyzing self-reported speeds and the results are shown in Figure 3. The non-parametric ANOVA type II revealed significant main effects of motor modes (Eco, Turbo) on reported speeds ($F(1, 98) = 20.198$, $p < .001$) and target speeds on reported speeds ($F(3, 98) = 11.899$, $p < .001$). However, there was no significant main effect for the interaction between motor mode and target speeds ($F(3, 98) = 1.135$, $p = .34$). The post-hoc analysis identified significant differences between both motor modes ($p < .001$) and significant differences between pairs of target speeds: 16 km/h vs. 22 km/h ($p < .001$), 16 km/h vs. 25 km/h ($p < .001$), 19 km/h vs. 22 km/h ($p = .012$), and 19 km/h vs. 25 km/h ($p = .009$). The power analysis for the main effect of motor mode showed that a sample size of $n = 13$ samples per mode is required to detect an effect size of $f = 0.595$. For the target speeds, $n = 6$ samples per speed are required ($f = 0.762$). For the interaction between motor mode and target speed, our study was underpowered, since $n = 29$ samples per group were required

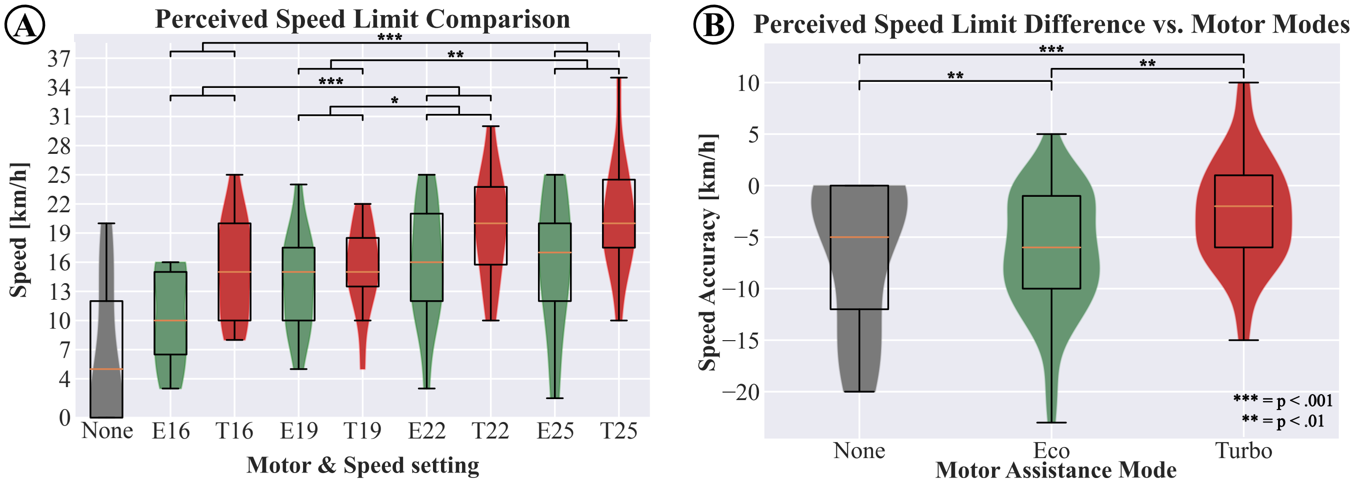

Figure 3: Perceived speed comparison. A shows the reported speeds after each trial and B the normalized reported speed distribution for each motor mode.

to detect an effect size of $f = 0.254$. Figure 3A illustrates the relationship between the reported speed and the target speed and the motor mode. The speed responses in Turbo mode tend to be higher than those in Eco mode at the target speeds.

For the comparison with None mode, we subtracted the target speeds from the reported speeds in Eco and Turbo mode. In None mode, we adopted a speed limit of 0 km/h and subtracted the reported speeds to account for the absence of electrical assistance. A Friedman's test showed significant differences of the three motor modes on the reported speeds ($Q(2) = 43.93, p < .001$). The Kendall's W value of $W = 0.366$ suggest that there is a moderate effect in how the motor modes affect the speed report. The subsequent post-hoc test identified significant differences between all comparisons: Turbo and None ($p < .001$), Turbo and Eco ($p = .003$), and Eco and None ($p = .003$). The noticeable discrepancy can be readily observed in Figure 3B. On average, participants consistently underestimated speed limits across all modes ($M = -4.61km/h, SD = 2.4km/h$). Notably, Turbo mode exhibited more accurate speed reports ($M = -2.7km/h, SD = 1.45km/h$) compared to Eco mode ($M = -6.52km/h, SD = 1.47km/h$). Six participants correctly identified that no assistance was provided when cycling in None mode and reported a speed of 0 km/h. Four participants reported in None mode a brief initial assistance, resulting in reported values of 5 km/h.

5.4 Workload Assessment

To analyze the workload, we grouped all raw calculated TLX scores into the modes None, Eco and Turbo. A Friedman's test indicated significant differences among the three groups ($Q(2) = 18.14, p < .001$). The Kendall's W value of $W = 0.151$ suggest that the agreement in the rankings of TLX scores across the motor modes is weak and the consistency of these differences is not very strong. The post-hoc test revealed no significant differences between Turbo and Eco mode ($p = .569$), while each was found to be significantly different when compared to None ($p < .001$). The raw TLX score was lowest in Turbo mode ($M = 34.67, SD = 15.14$), followed by Eco ($M = 38.22, SD = 15.4$) and None ($M = 46.89, SD = 11.88$). From the evaluation it can be stated that the workload was significantly lower when motor support was present. The results and corresponding TLX constitutes with the corresponding variability whiskers among our participants are shown in Figure 4A. Specifically, physical demand (PD), performance (P), effort (E), and frustration (F) contributed to the higher TLX scores in None mode.

We further analyzed whether our participants tried to cycle more intensely when the motor assistance was switched off. This was assessed by repeatedly asking them after each trial to respond on a 5-point scale from totally disagree to totally agree. A Friedman's test on the different support modes Eco, Turbo and None indicated significant differences among the groups ($Q(2) = 11.32, p = .003$). The very low Kendall's W value of $W = .094$ suggest no or weak agreement between the motor modes. The post-hoc test revealed a significant difference between Turbo and None ($p = .013$), while Turbo and Eco ($p = .726$) as well as Eco and None ($p = .089$) were not significant. The results are shown in Figure 4B in question A. We also repeatedly asked the question if they noticed when the assistance switched off. The Friedman's test indicated significant difference between the three support modes ($Q(2) = 75.82, p < .001$). The high Kendall's W value of $W = 0.63$ suggest a strong trend between the motor modes. The post-hoc test showed a significant difference between all pairs ($p < .001$). The results are shown in Figure 4B in question B.

5.5 Questionnaire

To enhance our comprehension of cruise control for e-bikes and to investigate prospective future applications, we incorporated supplementary inquiries into the concluding questionnaire, as depicted in Figure 5. Feedback from our respondents indicated that the motor disengagement had minimal impact on their cycling stability and control over the e-bike. Furthermore, the majority did not report a feeling of being controlled by the e-bike. Opinions on familiarity with e-bike riding and the accuracy of reported speed limits varied among respondents. When the motor switched off, 13 respondents

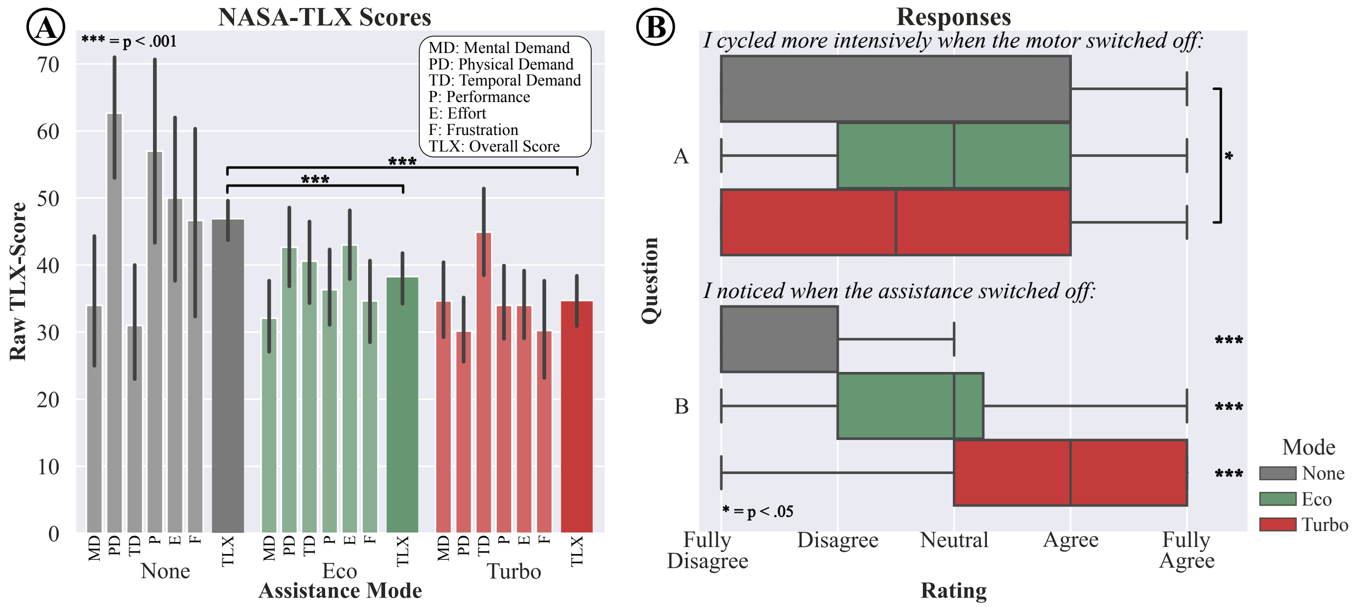

Figure 4: Raw NASA-TLX scores (left) and reported behavior and perception of the motor disengagement (right). The Turbo mode achieves the lowest workload and can be easily noticed. Questions A and B in the right figure are mentioned above the corresponding responses.

agreed that further manual accelerations became challenging. Nine participants reported that they could envision using such technology on their daily trips, while only one strongly disagreed with the idea of having dynamic support for e-bikes. Dynamic speed limits for optimized traffic signal phases and motor disengagements for warnings, such as overtaking vehicles, emerged as the most appealing use cases. However, motor disengagements during phone calls and headphone use were considered less appealing by the majority of our participants. For swarm scenarios, we gathered diverse opinions on our technology. When cycling in swarms with acquaintances and friends, our respondents more likely expressed positivity, whereas cycling in groups with strangers was rather disliked. Overall, participants agreed that dynamic speed control could enhance traffic safety, with only one individual expressing disagreement. Sharing bicycle data raised privacy concerns for half of our respondents. In the free comment field, one respondent mentioned experiencing varying speed limits during individual trials. Another participant expressed frustration with sudden motor disengagements, and one person expressed interest in testing the application in everyday traffic.

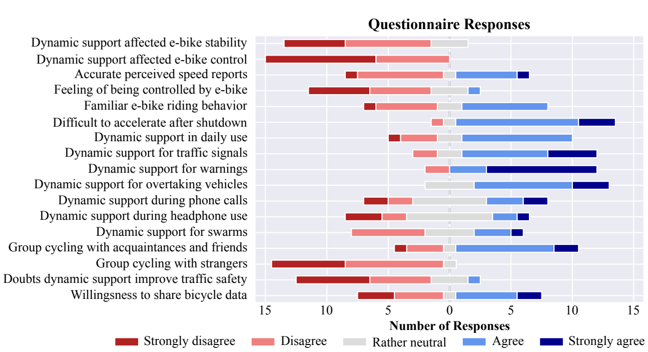

Figure 5: Questionnaire responses. On a five-point scale, we evaluated different questions regarding future use cases and the e-bike cycling behavior. The questions were simplified for a better readability. The complete set of questions can be found in the Appendix.

6 DISCUSSION

Our study demonstrated the ability of motor disengagements to control the speed of e-bike cyclists while perceived speed limits were on average rated lower than the actual cycled speed. The workload was most affected by the presence or absence of electrical support.

6.1 Challenges in Maintaining Cycling Speed Limits

Maintaining a desired cycling speed limit without visual speed feedback can be challenging. Our obtained average SUS score of 73.33 may have been influenced by the absence of a speed monitoring display and the repeated question of the perceived cycled speed limit. Participants often commented that they were unsure of the speed up to which they were being supported, which can also be inferred from the responses of Figure 5 under 'Accurate perceived speed reports'. Visual speed feedback [73] requires continuous monitoring which increases cognitive load. Without electrical support, we found that our participants showed a high variability of preferred cycling speeds, but were able to maintain their own preferred speed most accurately. With active electrical support, we were able to control the speed of the cyclists. In Turbo mode, our participants were slightly more accurate in maintaining a desired speed than in Eco mode. This observation can be attributed to the more conspicuous motor disengagement feedback with higher engine power. From the final questionnaire in Figure 5, we infer from the first two questions that the motor disengagements have a minor impact on the stability and control of the e-bike. One participant party exceeded our set speed limit and remarked a preference for higher speeds. On average, all cyclists mostly undervalued speed limits. The evaluation of speed reports indicated that a larger sample size is needed to accurately analyze interaction effects of motor modes and target speeds on reported speeds. However, we found that cyclists' speed perceptions were influenced by higher levels of motor support. A more powerful engine can result in higher estimated speeds. In addition, motor disengagement was more noticeable at higher power levels. This may explain the interaction effect of motor mode and target speed on the measured speeds, together with the participants' willingness to follow the instructions given by the e-bike. This also raises the future research question of whether this form of haptic feedback can be embedded into e-bikes for further notifications.

6.2 Factors Affecting Workload

The workload was influenced by the presence and power of electrical support, attributed to the additional effort required, and the potential frustration experienced in the absence of support. Between Eco and Turbo mode, we identified no significant difference in the workload. However, given the overall scores differed among the support modes, there is a possibility that with a larger sample size or different bike types, a significant difference could be observed. The obtained raw TLX scores ranging between 34 to 47 are comparable with related works on sporting activities ranging in between 40 to 50 [26, 33, 37] as well as lab studies analyzing input technologies in VR simulators ranging between 31 to 55 [29, 39, 48]. As our experiment was conducted outdoors, additional variables such as traffic, day time, and weather could influence our measured scores. Hence, our study design aligns with a more realistic use case. Additionally, our average measured speed of cyclists without electrical support ($M = 18.96km/h$) is similar to findings in related works ($M = 18.4km/h$) [9]. The measured cadence of approximately 60 rpm is known to be a pleasant pedaling rate with minimal physiological demand, as indicated by previous studies [2, 15].

6.3 Cyclists' Impressions of E-bike Modes

Upon reviewing the adjusted speed limits, we observed that cyclists maintain the speed limit of 16km/h less accurately, as depicted in Figure 2A. This may be related to riding below the usual and comfortable speed [9]. Two participants independently described cycling at 16km/h in Eco mode as "Granny mode", and four respondents associated the word "quiet" with the e-bike behavior. Maintaining a speed of 22 km/h, as previously used in a study [4], demonstrated the highest accuracy in Turbo mode. This speed limit was described by eleven participants as "dynamic", "lively", and "sporty". At 19km/h in Eco mode, ten participants remarked cycling as "comfortable" and "balanced". Without electrical support, nine participants associated cycling with "stressful" and "strenuous".

6.4 Factors Influencing the Accuracy of Dynamic Speed Control in Future Applications

For future applications that integrate traffic light signal phases into dynamic speed control, we derive that the accuracy of speed maintenance is influenced by both the target speed limit and the level of torque provided by the electric motor. However, the fluctuation effects around a certain target speed between different motors can be small. The distinct perceptibility of the motor disengagements and the cyclist's willingness to follow instructions are more crucial factors for CC. We observed that participants who overlooked the subtle feedback in Eco mode or ignored the instructions tended to ride at their preferred speed. Especially at lower speeds and with less engine power, higher speed fluctuations must be taken into account to ensure a seamless green wave for cyclists. This may be due to the frustration involved when the motor disengages below a cyclist's preferred speed. Moreover, it's essential to note that additional factors, such as varying traffic conditions [9], road surfaces [23], road inclination [63], weather conditions and different rider types [41] may additionally affect a cyclist's ability to maintain a consistent speed in daily traffic. In the context of swarm cycling, further research is required to ascertain whether groups of cyclists can maintain speed more accurately using CC compared to conventional cycling. The absolute fluctuations around a target speed remained within a comparable range when using CC. This may enable mixed groups of regular bicycles and e-bikes to maintain a cohesive formation when the speed of the regular cyclist is used to control the e-bike's target speed. Our questionnaire revealed distinct differences in participants' preferences regarding the formation of swarms with other cyclists. Our participants expressed a preference for cycling with friends, whereas cycling in groups with strangers was generally disliked. This suggests that swarm applications in urban areas [54] may need to facilitate connections between cyclists or form ad-hoc groups based on shared interests or riding styles. Integrating social networking features could help cyclists connect with others who have similar preferences or skills. Additionally, features that promote cooperation, communication and coordination among cyclists within a swarm, e.g. urban gamification [43], could help alleviate discomfort or reluctance associated with riding in groups with strangers. Moreover, it is crucial to consider how conventional cyclists can synchronize with swarms consisting of dynamically speed controlled e-bikes. One solution could involve virtual swarm centroids traveling along a predefined route [66]. However, leveraging smartphone GPS data to measure speeds and then share measurements with surrounding bicycles, could raise privacy concerns. Our respondents exhibited diverse opinions regarding the sharing of data, as depicted in Figure 5 in the last question. Furthermore, it remains of research how visual speed feedback influence the workload and speed accuracy for the proposed scenarios. A conventional speed display mounted on the bike or an AR head-up display embedded in a helmet [51, 80, 82] could be used for further research.

6.5 Limitations

This pilot study has a few limitations. First of all, the number of 15 participants was too small e.g. for detecting main effects of the interaction between the two motor modes (Eco, Turbo) and target speeds on the reported speeds. By comparing all reports grouped by each mode, including the None mode without assistance, we were able to identify significant differences in speed perception. However, to conduct a more detailed analysis of different target speeds and associated speed perceptions as a function of motor mode, the number of participants needs to be increased. Secondly, the number of female cyclists, as well as the number of experienced and inexperienced e-bike cyclists preclude a more detailed statistical comparison. Variations in cycling behavior [7, 41, 79], cycling regularity and average route length [56], and cultural acceptance of new technologies [35] further complicate establishing generalizable results across all potential user groups [18, 32]. Furthermore, our study was conducted in low traffic situations on flat terrain. External factors such as road inclination [63] would have potentially influenced the data collection.

7 CONCLUSION

This paper investigated the accuracy of maintaining a designated speed limit with e-bikes through active motor control for application scenarios such as swarm cycling and optimized traffic signal phase control. A pilot study involving 15 participants was conducted to evaluate workload, perceived speeds, and speed measurements across target speeds ranging from 16 to 25 km/h, under varying levels of electrical assistance.

We observed that cyclists can accurately maintain a specific speed through active motor control, even without explicit knowledge of the current speed. Concurrently, cyclists tend to underestimate their speeds, which is also influenced by the power of the engine. Furthermore, we found that the accuracy of maintaining a dynamic set speed limit is higher with increased motor power, while the workload is lowest, which is related to the conspicuousness of engine disengagements. The use case of optimized traffic signal phases was preferred over swarm cycling applications in our questionnaire. Our participants reported a preference for cycling together in groups of people they know. Further research is needed to investigate the impact of visual speed feedback on cyclists' speed accuracy and the viability of dynamic speed adjustments based on traffic and swarm cycling. Additional urban pilot studies with varying traffic signals and cyclist swarms will provide insights into the effectiveness of cruise control for cyclists.

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A CLOSING QUESTIONNAIRE

Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Switching off the motor affected my cycling stability.					
I was able to control the e-bike well.					
I had the feeling that I could estimate the speed well while riding.					
I had the feeling of being controlled by the e-bike.					
I was able to ride the bike the same way I use to ride my bike in everyday life.					
After the support was switched off, it was difficult to continue to accelerate.					
In everyday life, switching off support in general wouldn't bother me.					
If the motor shutdown would help me drive more at green lights, I would use it.					
If the motor shutdown could warn me of danger, I would use it.					
The motor shutdown would be helpful to warn me of approaching vehicles.					
I would accept a motor shutdown if I talk on the phone while cycling with one hand.					
I would accept a motor shutdown if I listen to loud music on headphones while driving.					
I like to ride right next to someone I know.					
I like to ride right next to someone I don't know.					
In groups with e-bikes and regular bicycles it is difficult to maintain a common pace.					
I can't imagine that a technology like this would make traffic safer.					
In everyday life it wouldn't bother me to share trip data with local route operators.					