Using Physiological Sensors and Infrared Imaging in Evaluations of the Impact of Smart Cycling Technologies on Cycling Experience

Mario Boot

Civil Engineering, Faculty of Engineering Technology, University of Twente, m.r.boot@utwente.nl

BARAN ULAK

Civil Engineering, Faculty of Engineering Technology, University of Twente, m.b.ulak@utwente.nl

Karst Geurs

Civil Engineering, Faculty of Engineering Technology, University of Twente, k.t.geurs@utwente.nl

Paul Havinga

Pervasive Systems, Faculty of Electrical Engineering, Mathematics, and Computer Science, University of Twente, p.j.m.havinga@utwente.nl

"Smart cycling technologies" (SCTs) that support cyclists while cycling outdoors are on the rise, and it is important to evaluate their impact on cycling experiences. This research therefore aims to develop a framework that guides evaluations of the impact of SCTs on cycling experience. A key question is if and how wearable body sensors can deliver valuable input for such evaluations. Research methods are a systematic literature review, research through design, and empirical studies. Results so far are a conceptualization of the framework for evaluations, a study about measuring and supporting shared flow in cyclists, and a study about predicting pleasantness ratings from data about brain oxygen consumption. Next steps are to develop a mixed method sensor system to measure experiences with an SCT, and to develop a data analysis method that moves beyond understanding correlations towards cause-effect relationships in experiences with SCTs.

CCS CONCEPTS: **Human-centered computing – Empirical studies in HCI; interaction design; ubiquitous and mobile computing**

Additional Keywords and Phrases: Cycling; smart cycling technology; experience; causal analysis; evaluation

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1 NEED FOR EVALUATIONS OF SMART CYCLING TECHNOLOGY

Many countries worldwide are interested in promoting cycling usage and safety, leading to a growing interest in Smart Cycling Technologies (SCTs). SCTs, utilizing Internet of Things and Artificial Intelligence features, assist cyclists throughout their rides (Berge et al., 2023; Kapousizis et al., 2022; Nikolaeva et al., 2019; Oliveira et al., 2021). Examples include speed adaptation and collision avoidance systems. These technologies are increasingly integrated into bicycles. Understanding the impact of SCTs on cycling experiences is crucial as they gain prominence.

Cycling experiences – emotions, feelings, etc. experienced during cycling – have received limited research attention in transport research (Das et al., 2017; van Hagen et al., 2019). Cycling experiences are important to study because they interact with travel behavior and wellbeing. E.g., perceptions of unsafe conditions can discourage frequent cycling (De Vos et al., 2013; Heinen et al., 2010; Mokhtarian, 2018; Popan, 2020; van Hagen et al., 2019).

To gain insights into cycling experiences, researchers are turning to wearable biosensors (Lai et al., 2013; Lim et al., 2022). These sensors, directly connected to the human body, can measure variables like heart rate, breathing, brain activity, and body movements. They provide real-time data, unlike crash statistics and questionnaires (Ryerson et al., 2021). Also, the physiological data from these sensors can make insights in subjective experiences more objective and are increasingly used in user experience evaluations (Iriarte et al., 2021).

While some studies have used body sensors to assess the effects of SCTs on cycling, several knowledge gaps remain. Further exploration is needed to determine how well body sensor data can be linked to specific types of cycling experiences (Bigazzi et al., 2022; Lim et al., 2022). It is not well understood if sensor data can effectively capture the effects of SCTs on cycling experiences, and the presence of confounding factors complicates establishing cause-effect relationships. Additionally, the real-time utilization of sensor readings for control systems in bicycles is an emerging area that warrants further attention (Andres, 2020).

To address these knowledge gaps, our research has several aims. Firstly, we aim to develop a conceptual framework that can guide evaluations that use body sensor data to determine the influence of SCTs on cycling experience. Secondly, we aim to validate the framework via case studies in which experiences with SCTs are measured and evaluated. Next sections summarize the framework, case studies, and next steps.

2 CONCEPTUAL FRAMEWORK FOR EVALUATIONS

The framework is based on a systematic review of existing literature about body sensors for cycling experience evaluations. The evaluation framework is shown in Fig. 1. The framework explains that evaluations should consider factors and methods in four categories: 1) experiences with SCTs, 2) experience measurements, 3) causal analysis, 4) confounding variables. One key part of the framework – not visualized but described in a research article that is currently in revision – is that a mapping is made between which types of experiences can be analyzed with which type of sensors. Next to the conceptual framework, we highlight two case studies which illustrate the validation of the framework in practice.

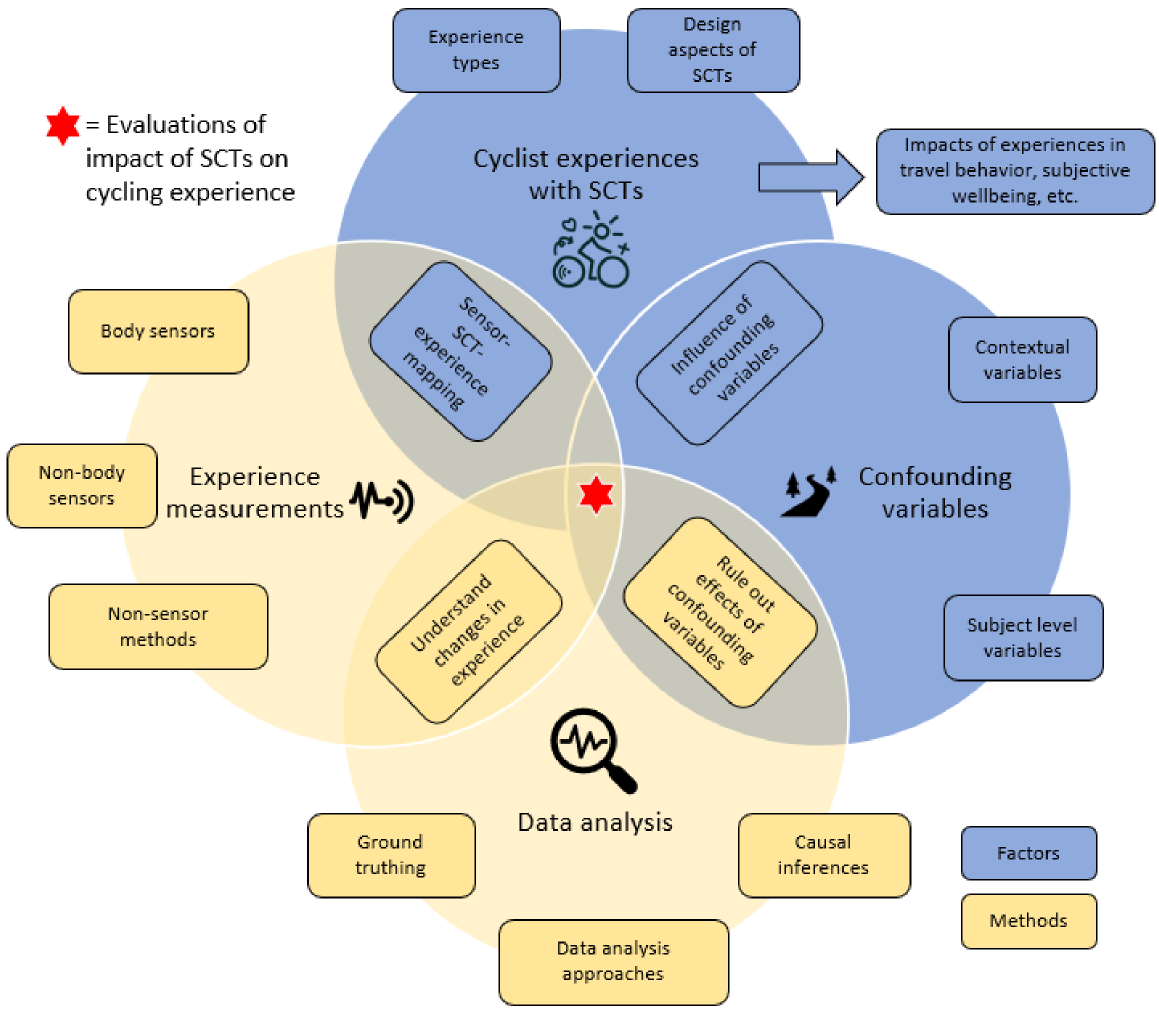

Figure 1 - Conceptual framework of factors and methods in evaluations that use body sensor data to determine the influence of Smart Cycling Technologies on cycling experience.

3 CASE STUDY 1 – UNDERSTANDING AND SUPPORTING SHARED FLOW IN GROUPS OF CYCLISTS.

The first case study is about shared flow in groups of cyclists. Shared flow is a highly desirable state characterized by strong enjoyment, a shared state of balance, and joint synchrony in behavior and experience among group members (Csikszentmihalyi, 2013; Salanova et al., 2014; Tian et al., 2017). Differences in various skill limit shared flow, while so-called balancing systems may even out skill differences. Therefore, we conducted an outdoor study to determine how to measure shared flow, and how to support shared flow with a balancing system. The experimental study in which various variables (Figure 2) were measured in 21 older adult cyclists led to interesting results. It turned out that cadence and relative position indicated shared flow, while heart rate did not. Figure 3 shows various outcomes from the statistical analysis of correlations between the probability of shared flow and measured variables. Further research should investigate more intricate dimensions of shared flow like collective efficacy and distortion of time perception.

Variable measured	Brand	Model	Method	Sampling rate	Moment of collection
Autotelic personality score	x	x	Autotelic Personality Questionnaire	x	Before the cycling rounds
Position	GoPro	Hero 5	x	30 frames/second	During the cycling rounds
Heart rate	Empatica	E4 wristband	x	1 Hz	During the cycling rounds
Cycling cadence	Wahoo	RPM cadence sensor	x	1 Hz	During the cycling rounds
Video for shared flow recall	Motorola	Moto G 5G Plus	x	30 frames/second	During the cycling rounds
Shared flow per 30 second interval	x	x	Flow timeline	30 seconds	After each cycling round
Percentage of time spent in shared flow	x	x	Flow timeline	x	After each cycling round
Intensity of shared flow	x	x	Shared Flow Scale	x	After each cycling round

Figure 2 – Overview of data collection methods used in case study 1.

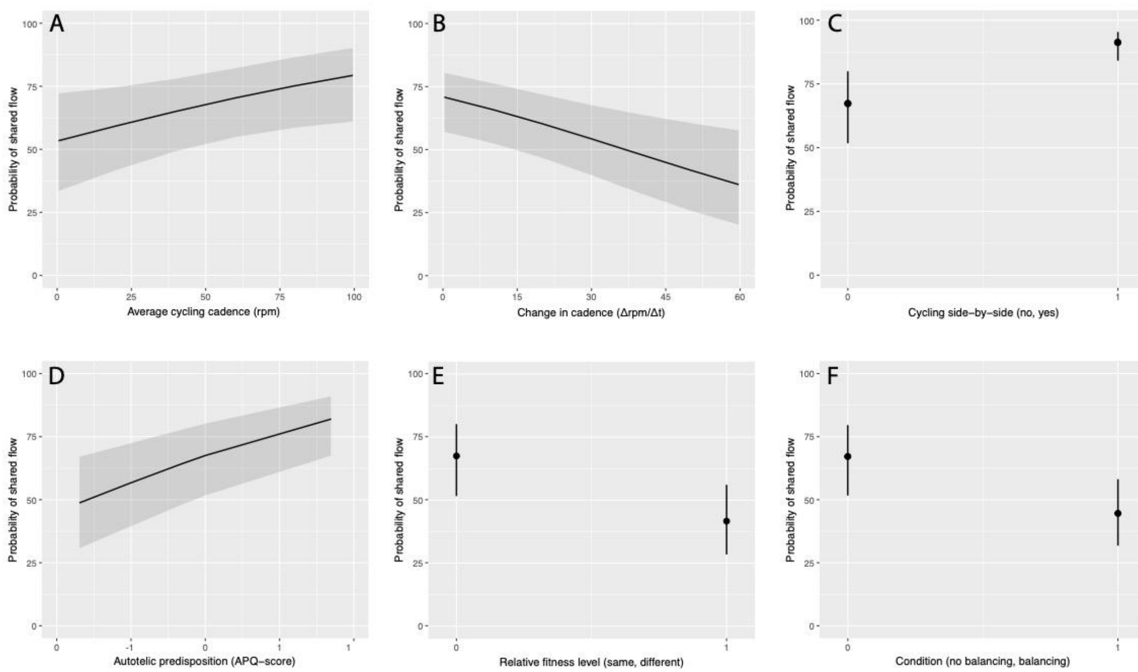

Figure 3 - Outcomes from the statistical analysis of correlations between the probability of shared flow and measured variables.

4 CASE STUDY 2 – MEASURING THE RANGE OF PLEASANTNESS-UNPLEASANTNESS VIA WEARABLE INFRARED BRAIN IMAGING.

The second case study about measuring cycling experience concerns the use of functional near-infrared spectroscopy (fNIRS). fNIRS is a non-invasive and highly portable neuroimaging technique that measures changes in brain blood oxygenation levels using near-infrared light (Balardin et al., 2017; Boas et al., 2014; Piper et al., 2014). We conducted a study with 17 participants. Data was collected via a fNIRS system, self-reports, and interviews to investigate the potential of using oxygenation data for differentiating between positive and negative pleasantness experienced during cycling. A visual inspection of collected data (Figure 5) shows that unpleasant ratings relate to higher variability in brain oxygenation than neutral and pleasant ratings. Specific brain regions show specific oxygenation levels for different ratings. Statistical results about correlations between oxygenation levels and self-reports were computed however reliability of these results is difficult to assess due to immature data preprocessing and analysis toolkits. The results show the feasibility of using fNIRS in cycling experience research. Future work is necessary about what “pleasantness” during cycling is exactly, and about data preprocessing techniques.

Figure 4 – A fNIRS headcap on a cyclist with one of our researchers.

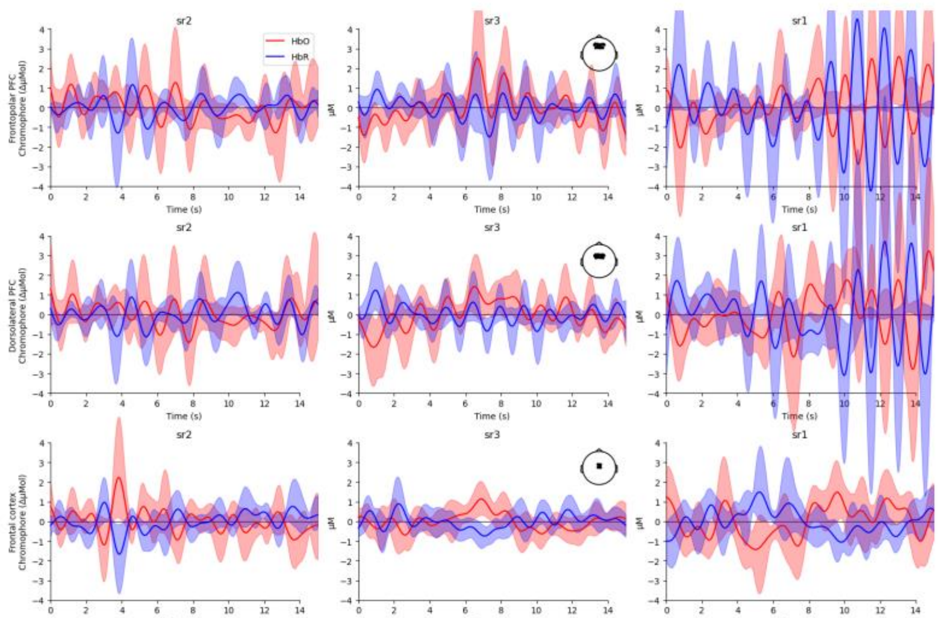

Figure 5 – A visualization of brain oxygenation levels for three brain regions and three pleasantness ratings.

5 NEXT STEPS

Next steps in the research are to integrate multiple sensor types and experience sampling into a mixed-method measurement approach. This approach will also include non-sensor methods to gather data about confounding variables form the environment and participants (e.g., experience sampling, street crowdedness, weather, age, attitudes). Then, the plan is to use the experience measurement approach together with a form of SCT to measure and evaluate the resulting experiences. Lastly, statistical methods will be developed for causal analysis, to develop a method for determining how SCTs cause changes in cycling experiences.

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