RiderID: Investigating Cycling as a Behavioral Biometric through Bicycle-Mounted Sensors

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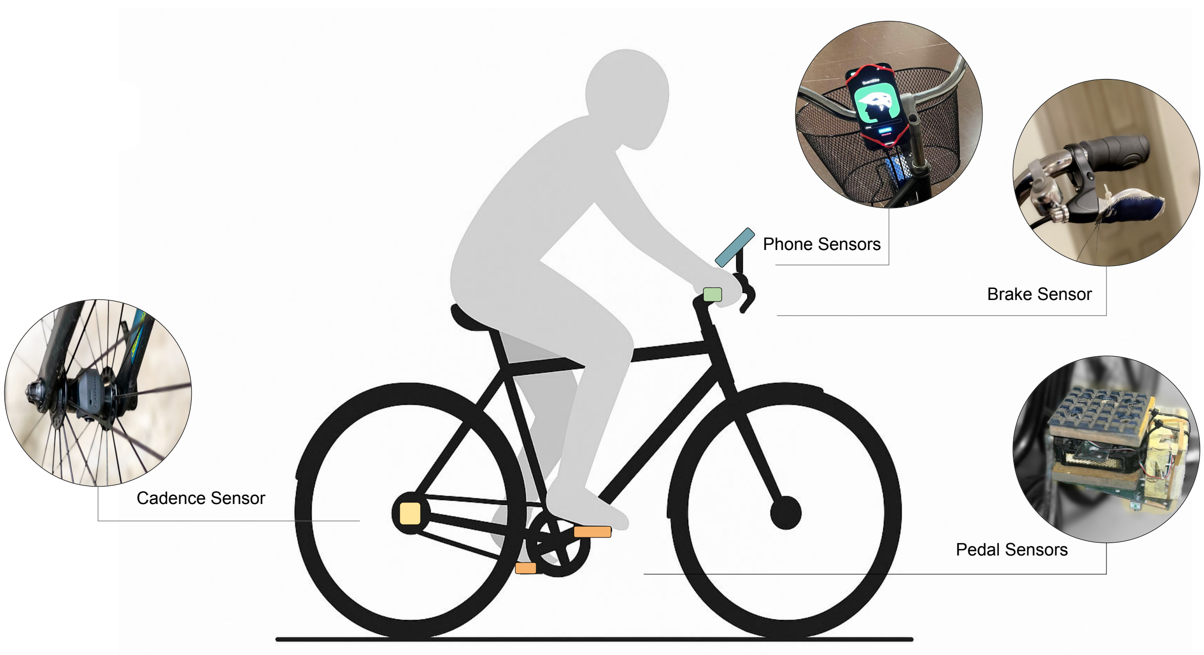

Figure 1: Cycling as a behavioral biometric: we captured rider patterns with bicycle-mounted sensors, including force sensors on the pedals and brakes, cadence sensors, and phone-embedded motion sensors, across controlled and in-the-wild tracks.

Abstract

Despite their ubiquity, bicycles remain largely unexplored as a space for personalization and cyclist-aware solutions. Since cycling is inherently a behavioral activity, we investigate its potential as a biometric trait for continuous identification and personalization. For this, we mounted multiple sensors on a regular bicycle and conducted an outdoor experiment (N=16) across two sessions on two cycling tracks: a short, controlled track and a long, in-the-wild setup. This design enabled us to examine how stable cycling patterns are across sessions and how well individuals can be distinguished in controlled versus real-world conditions. Our findings demonstrate the feasibility of leveraging cycling behavior for continuous identification and personalization, achieving identification accuracies of up to 94.3%. We discuss the implications of these results for real-world deployment, as well as the challenges posed by environmental factors, rider variability, and the need for robust and unobtrusive sensing solutions.

CCS Concepts

• **Human-centered computing** → **Interactive systems and tools**.

Keywords

behavioral biometrics, cycling, bicycle-mounted sensors, rider personalization

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1 Introduction

Cycling has emerged as a key area within HCI research, motivated by its potential to promote sustainable, healthy, and safe mobility. Prior work has investigated how to support cyclists through multimodal feedback [55], smart assistance systems [53], and immersive simulations [11], while also highlighting the complexities of studying behavior and perception in dynamic, real-world environments [22, 79]. Despite advances in cycling systems, bicycles remain largely non-personalized and unaware of their users. Unlike other personal devices such as smartphones or smartwatches, they cannot identify riders or adapt to individual preferences and needs. This absence of user-awareness limits personalized support, such as assistance levels, feedback modalities, or safety interventions based on the rider's experience, fitness, or behavior. As cycling technologies evolve, there is a growing need to treat bicycles as interactive systems, capable of recognizing, adapting to, and protecting their riders in a dynamic and user-centered approach.

In this context, behavioral biometrics are emerging as a promising approach for adaptive and user-aware cycling systems. Unlike traditional authentication methods, behavioral biometrics leverage patterns in users' actions, such as movement, posture, or interaction style, that are often implicit, continuous, and difficult to replicate [23, 30, 65]. This makes them particularly suitable for dynamic environments such as cycling, where hands-free and unobtrusive recognition is essential. By capturing and analyzing behavioral signals, such systems can enable personalized assistance, adjust settings in real-time, and, crucially, distinguish between authorized and unauthorized users. This dual function enhances both the usability and security of bicycles, supporting context-aware safety interventions tailored to the individual, while offering protection against potential misuse. As sensor technologies and onboard processing capabilities become more accessible, integrating behavioral biometrics into cycling holds great potential for advancing intelligent, rider-centric mobility solutions.

In this paper, we explore the idea of capturing cycling behavior by embedding multiple sensors (accelerometers, cadence, and force sensors) on key components of the bicycle (the pedals, steering, and wheels) (Figure 1). This setup enables the collection of rich, fine-grained behavioral data that reflects the rider's unique movement patterns and interaction dynamics with the bike. To evaluate this approach, we conducted a study (N=16) involving realistic riding scenarios across two distinct tracks: a short (∼114 m) lemniscate and enclosed track designed for controlled conditions, and a long (∼1495 m) outdoor track representing real-world variability. These settings enabled us to capture behavioral signals under diverse environmental conditions, supporting controlled and field-level data collection. Objective performance metrics highlight the strong potential of cycling behavior as a form of behavioral biometric, with an average accuracy reaching up to 94.2% for the short track. We also observe a major change when evaluating the behavior between sessions, with accuracy dropping to an average of 33.2%. This is also common with the other behavioral traits, where accuracy performance drops with intra-session evaluations [23]. Additionally, participants expressed strong interest in the concept of sensor-embedded bicycles for behavioral identification, with most indicating they would be interested in acquiring such a bike. These subjective findings highlight both the practical challenges of cycling as a biometric and the potential openness to integrating sensing technologies into everyday riding. These insights confirm the cycling behavior's ability to continuously and implicitly identify the riders and provide a valuable foundation for understanding user intent, habits, and context. We propose a novel approach to investigating cycling as a behavioral biometric and present the first empirical study of its feasibility for continuous implicit identification. Our findings show that steering and pedaling dynamics provide the strongest identification cues, informing minimal sensor configurations for real-world deployment.

2 Related Work

In this work, we investigate cycling as a distinctive behavioral trait built on two pillars of previous work: (1) cycling in Human-Computer Interaction and (2) biometric-based identification.

2.1 Cycling in HCI

Cycling has been widely studied in HCI as a means of promoting sustainable, safe, and healthy mobility. Research has primarily focused on improving safety, with studies investigating how cyclists receive warnings, navigation assistance, and traffic-related information. Habib et al. identify three key components that shape cycling performance–behavior, workload, and perception–all of which directly impact cyclists' safety [25]. Various feedback modalities have been explored to support cyclists, including visual cues [42], auditory cues [5, 42], and vibro-tactile feedback [32, 41, 42, 54, 61, 62]. In addition to safety, cycling is also recognized as an effective form of healthy mobility [26, 31] and a beneficial exercise for improving overall health [17, 18, 24, 73, 74]. While researchers have derived valuable insights into designing CyclingHCI systems [56], the field continues to face significant challenges [44].

Tracking and analyzing cycling behavior require defining the relevant data sources and measurement techniques. Various sensor-based approaches have been used to capture physiological and behavioral data, including hand gestures and head movements for interaction and safety [19, 43, 61]. Cycling behavior has been studied using bicycle ergometers in VR exergames [27, 51] and by attaching custom sensors to existing (indoor) bicycles for motion and exertion tracking [6, 7, 28, 57]. Gamification and interactive training systems further leverage real-time sensor data, particularly in indoor cycling setups [4, 15], where cycling behavior is measured using sensor-equipped direct-drive and on-wheel trainers [9] or even a smartphone-based approach [15]. Beyond individual sensors, bike trainers have been augmented with additional actuators to simulate real-world cycling dynamics [45–47, 50, 75]. These systems extend to bicycle simulators, integrating screens or VR to enable controlled studies of cycling behavior [9, 37, 41, 68, 75], including research on motion sickness reduction [50]. As an extension, tandem-based simulators have been introduced to explore future cycling experiences with self-driving bicycles [46, 48, 76] and interactions with other cyclists and road users [69, 70], as well as AR applications in cycling [49]. The integration of physiological sensors has further enhanced CyclingHCI by providing real-time data, including vital signs [12, 16], vision enhancement [8], and posture support [6]. Systems have also explored real-time heart rate visualizations [3, 70], stress [13, 67] and fatigue assessment [34, 64], helping to adjust and improve fitness levels dynamically [20]. Further, fabric-based sensors have been developed to track a cyclist's position, cadence, and knee joint angle [78]. However, the accuracy of physiological data collection in real-world cycling remains an open challenge. Electrodermal activity and heart rate variability as stress indicators have shown inconsistent reliability in outdoor settings [10, 40, 60], raising concerns about the robustness of such measurements.

While prior work has investigated tracking various cycling metrics for interaction, feedback, and training in CyclingHCI, individual cycling behaviors have not yet been explicitly explored for identification purposes. Integrating sensor technology and onboard computing, the potential for leveraging cycling behavior as a biometric trait becomes even more relevant. This paper builds on these findings by investigating cycling as a behavioral biometric, using sensor-equipped bicycles for continuous implicit identification.

2.2 Behavioral Biometric Identification

Biometric systems are designed to recognize individuals based on distinctive physiological or behavioral characteristics [29, 30]. Traditional physiological biometrics, such as fingerprints [66], iris scans [52], and facial recognition [36, 80], have been widely adopted across security domains due to their high accuracy and reliability. While behavioral biometrics focus on how individuals perform certain actions rather than what they are. Common examples include keystroke dynamics [59, 81], mouse movements [14], gait [71], and touchscreen interactions [35]. These traits are often more subtle, context-dependent, and suitable for unobtrusive monitoring, making them ideal for scenarios where continuous authentication is desired [33, 58, 77]. Recent work has also explored behavioral signals in multimodal interactions, leveraging combinations of motion, posture, and device interaction to enhance recognition accuracy while preserving user comfort and natural behavior [1].

Unlike traditional authentication mechanisms that are invoked at discrete moments (e.g., login), continuous and implicit identification systems operate in the background, validating user identity in real-time as a natural part of interaction [2, 38]. Such systems are particularly useful in mobile, wearable, and ubiquitous computing environments, where users frequently move across contexts and devices [72]. By leveraging behavioral signals that require no explicit action, these methods offer a seamless balance between security and usability. However, achieving robustness and scalability in real-world conditions remains an open challenge, particularly with noisy data, environmental variability, and ethical considerations surrounding transparency and consent [1, 39, 63].

2.3 Motivation and Research Questions

While previous work has leveraged cycling data for performance analysis, training support, or safety monitoring, no prior work has directly and systematically investigated cycling behavior as a behavioral biometric for continuous and implicit user identification. Behavioral biometrics offer the potential for seamless and privacy-aware personalization, yet most research has focused on activities such as walking, typing, or smartphone interaction. Cycling, as a naturally rich and periodic motor activity, remains an underexplored source of identifiable behavioral patterns, particularly in realistic, outdoor conditions and on non-electric bicycles. Motivated by this gap, we explore the idea of capturing cycling behavior in real-world scenarios using a bicycle equipped with sensors. We analyze this data to evaluate the feasibility of rider identification based on movement patterns, to enable secure, adaptive, and user-aware cycling systems with the following research questions (RQs):

- **RQ1** To what extent can cycling behavior be used as a behavioral biometric for continuous and implicit user identification?
- **RQ2** Which behavioral features contribute most to identification accuracy, and how can this knowledge guide the design of minimal and practical sensor configurations for real-world deployment?

3 Investigating Cycling as a Behavioral Biometric Identifier

Guided by our research questions, this work explores the feasibility of cycling behavior as a behavioral biometric for continuous and implicit identification. We propose a proof-of-concept system that augments a bicycle with unobtrusive sensors to capture a rider's unique interaction patterns during real-world cycling. This approach is rooted in the hypothesis that individuals exhibit consistent, distinguishable cycling behaviors that can be recognized through fine-grained motion and force data collected at various points on the bike. Furthermore, by analyzing feature importance, we aim to understand which aspects of cycling behavior contribute most to identification accuracy, informing the design of minimal, scalable sensor configurations.

3.1 Study Design

We designed a within-subject study to investigate the feasibility of using cycling behavior for continuous, implicit identification in both controlled and real-world environments. Each participant completed a series of rides on two distinct tracks. First is a short, enclosed track that offered a stable and controlled setting, enabling consistent data collection with minimal external disturbances. Second is a long, outdoor track that introduced natural variability in terms of terrain, movement, road inclination, patterns, and environmental noise. This dual-track design allows us to explore how well cycling behavior can be captured and analyzed across ecologically diverse contexts. While environmental factors such as weather conditions (e.g., sunny, windy, rainy, and snowy) were not systematically controlled, they varied naturally between sessions and participants. This variation adds ecological realism to the dataset and enables us to assess the robustness and generalizability of identification models under real-world noise.

To evaluate the effectiveness of our approach, we focused on both objective performance metrics and subjective user feedback. The primary dependent variable is identification accuracy, which reflects the system's ability to recognize individual riders based on their cycling behavior. This is quantified using standard classification metrics, including accuracy, precision, recall, and F1 score. These metrics allow us to evaluate the feasibility of cycling behavior as a biometric trait for continuous and implicit user identification.

Additionally, we analyze feature importance scores derived from the model to determine which behavioral signals (e.g., pedal torque, cadence patterns) contribute most to identification performance. To complement the system-level evaluation, we collected subjective feedback from participants using post-ride questionnaires. Participants were asked to rate aspects such as comfort and acceptability of being identified based on cycling behavior. This feedback offers insight into the usability and user acceptance of the proposed system and informs future design considerations for deploying such technology in everyday cycling scenarios.

3.2 Apparatus

To capture cycling behavior, we equipped a bicycle (wheel diameter = 27 inch) with publicly available sensors positioned at key interaction points, including the pedals, handlebars, and wheels (Figure 1). This setup was designed to capture both upper- and lower-body engagement, reflecting behavioral traits such as pedaling rhythm, steering input, and braking force [21]. A *smartphone* (Apple iPhone 12, iOS 17) mounted on the handlebars acted as the central recording unit. Using a customized version of an open-source cycling application (*QuantiBike*[1]), it collected motion data from the phone's accelerometer, gyroscope, and GPS, while also receiving data from external sensors via a TCP server [47]. The *pedal sensors* consisted of 50 kg CZL635 load cells (RobotShop) integrated into custom pedal mounts and connected to ESP32-WROOM-32 microcontrollers (Espressif) equipped with Wi-Fi. Each circuit included an INA125P amplifier and a 3.7 V 1200 mAh Li-Po battery. The sensors measured pedaling force and transmitted values at 10 Hz without interfering with natural cycling behavior. The *brake sensor* was implemented as a flexible pressure sensor made of Velostat/Linqstat conductive film with copper tape leads, enclosed in a protective leather cover and attached directly to the brake handle. It measured braking force as voltage changes and wirelessly transmitted the readings to the phone. A Garmin Speed Sensor 2 was mounted on the hub to capture cadence and wheel rotation. The smartphone served as the central data logger, receiving inputs from the brake, cadence, and pedal sensors through Wi-Fi. External sensors were synchronized to the phone via timestamps. All devices are commercially available or open-source. All data streams, including pedals, brakes, cadence, and phone motion, were synchronized and logged by the *QuantiBike* app using timestamped key-value messages. All participants used a single, consistently equipped bicycle to ensure that observed differences reflected individual riding styles rather than hardware variation.

3.3 Cycling Tracks

To evaluate cycling behavior in both controlled and naturalistic conditions, participants cycled along two predefined tracks. The first was a *short track* representing a controlled setting. It followed a lemniscate (∞-shaped) path with a total length of approximately 114 meters, designed to capture steering maneuvers in both left and right directions. Situated in a flat, unobstructed area, the track enabled consistent and repeatable runs without external interruptions.

To simulate in-the-wild, realistic conditions, we defined a *long track* measuring approximately 1495 meters. This route followed an actual bicycle-friendly path around the university campus, exposing participants to variable terrain, pedestrian presence, and environmental noise. It also included both upward and downward slopes, providing a more authentic cycling experience. Both tracks are shown in Figure 2(b). This combination of tracks allowed us to capture steering patterns in both directions, investigate intra-user consistency in controlled environments, and examine behavioral variation in real-world conditions. For both tracks, we labeled the route with numbered sections to structure the paths and enable fine-grained reference during guidance and post-ride feedback collection. Participants were guided along these predefined, sectioned paths to ensure consistency across runs.

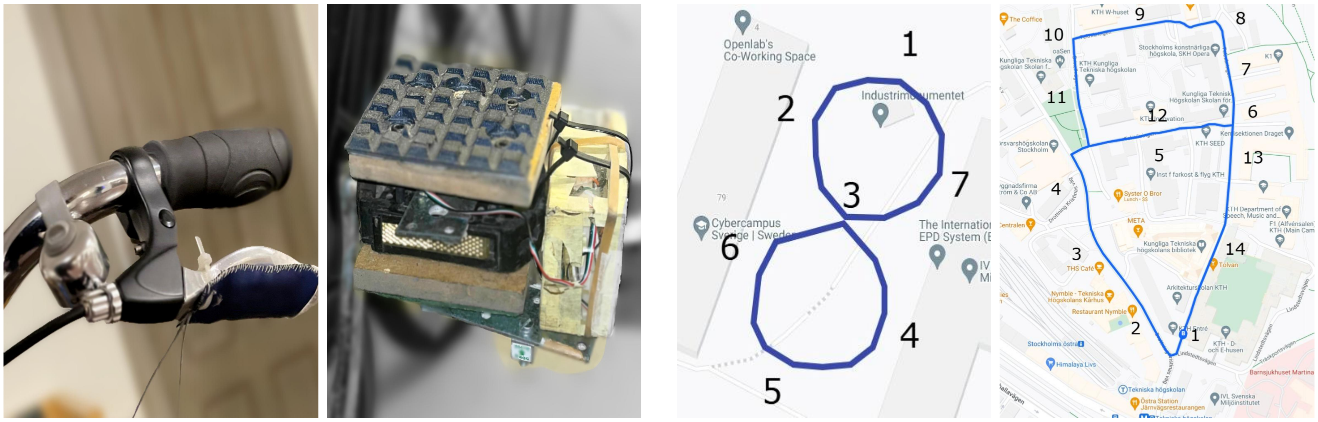
3.4 Study Procedure

Upon arrival at the study site, participants were welcomed and provided with an overview of the study. They first completed an informed consent form, followed by a short demographics questionnaire. To counterbalance potential order effects, eight participants began with the long track and seven with the short track. For each assigned track, participants were instructed to ride the instrumented bicycle in their normal cycling style. For the long track, the experimenter guided participants along the predefined route, which was divided into labeled sections to ensure consistent navigation and enable precise reference during post-ride feedback and analysis. For the short track, participants were instructed to complete five consecutive laps of the lemniscate path. After completing both tracks, participants filled out a post-ride questionnaire. This captured subjective feedback on their overall experience, any problems encountered, and specific sections of the track they found uncomfortable. Additionally, participants rated the comfort of the mounted pedal and brake sensors. The procedure was repeated for each participant on a second day, with an average interval of 36 days between sessions. The second session followed the same track order assigned on the first day, but did not include the post-ride feedback questionnaire.

3.5 Participants

We recruited 16 participants (age range: 19–37 years, M = 25.75, SD = 5.2; 4 female, 12 male, none self-identified otherwise) through university mailing lists and personal networks. Participants also reported their weight (M = 81.25 kg, SD = 19.69; range: 50–125 kg) and height (M = 177.43 cm, SD = 11.7; range: 154–198 cm). Participants were also asked about their cycling habits and bicycle ownership. Regarding frequency of use, most participants (7 out of 16) reported infrequent bicycle use (cycling less often). A smaller group reported frequent usage, with 2 participants cycling several times a day, 2 cycling 3–5 days per week, and 1 cycling 1–2 days per week. Four participants indicated they never cycle, were unsure, or chose not to respond. In terms of ownership, seven participants owned a regular bicycle, while nine did not own any bicycle (regular or electric). No participants reported owning an electric bicycle. Participation was voluntary, and each participant received a reimbursement of 10€ for their time. Informed consent was obtained from all participants per institutional ethical guidelines.

[1] https://github.com/Nomandes/quantibike



(a) (b)

Figure 2: (a) Close-up of the bicycle setup: the brake sensor (left) and the embedded sensing unit (right). (b) Study routes: the short controlled track (left), and the longer in-the-wild track (right) with 7 and 14 labeled sections, respectively.

4 Data Analysis

For each participant, we collected one recording of the *short track*, which included five repetitions, and one recording of the *long track*. Following a visual inspection of the recorded data, two participants were excluded due to faulty recordings. This resulted in a dataset of 168 files, corresponding to 14 participants across two sessions (10 short-track files and 2 long-track files per participant).

Table 1: Overview of extracted feature sets.

Feature Set	Description
All	Combination of all extracted features (sensor, frequency, and cycling-specific).
Sensor	Statistical descriptors (mean, std, min, max, IQR) from accelerometer, gyroscope, and quaternion signals.
Frequency	Spectral features—dominant frequency, total spectral power, and entropy—computed via Welch periodogram for IMU signals.
Pedals	Left–right force imbalance (mean, variability) from pedal load cells.
Brake	Braking frequency (rising edges) and duration ratio from brake pressure sensor.

4.1 Preprocessing

We filtered out irrelevant sensor channels (e.g., magnetic field, phone battery, and raw acceleration including gravity), retaining only motion, orientation, and cycling-specific signals (e.g., user acceleration, gyroscope, quaternions, pedal weight, cadence, velocity). This ensured that subsequent analysis relied solely on features directly related to cyclists' movements rather than device metadata or environmental noise. To address noise in the time-series signals, we applied signal-specific smoothing strategies. For fast-dynamic channels (accelerometer, gyroscope, and quaternion orientation), we used a Savitzky–Golay filter with a window length corresponding to approximately 1.5 s and a polynomial order of 2. This choice preserves local peaks and micro-variations in cycling motion while attenuating high-frequency sensor noise. For slower signals, such as GPS-based velocity, latitude/longitude, altitude, cadence, and pedal weight, we applied a rolling mean filter to smooth out jitter while retaining long-term trends. This mixed filtering approach reflects best practices in multimodal sensing, where preserving the fine structure of high-frequency dynamics and stabilizing low-frequency contextual signals are essential for accurate behavioral modeling.

4.2 Feature Extraction

After preprocessing, we transformed each lap of the short track and each long track into a compact numerical representation by extracting a set of descriptive, frequency, and cycling-specific features. The resulting feature vector summarizes the cyclist's behavior per session while discarding route-dependent signals such as GPS coordinates (latitude, longitude, altitude) and mobile phone meta-data. Each dataframe was thus reduced to a single feature vector, which formed the basis for our machine learning analyses.

We selected *sensor descriptive features* for motion (user acceleration, gyroscope) and orientation (quaternions). For each signal, we computed mean, median, standard deviation, minimum, maximum, and interquartile range (IQR), resulting in 78 features. We also calculated vector magnitudes (e.g., acceleration magnitude, angular velocity magnitude) and their descriptive statistics (N=4). Next, we derived *frequency-domain features* to capture periodic patterns in cycling dynamics. Specifically, we computed the dominant frequency (Hz), spectral entropy, and total spectral power from the acceleration and gyroscope signals using Welch's method, resulting in a total of 21 frequency features. These features characterize rhythmic pedaling-like oscillations, variability, and the energy distribution in the frequency spectrum. Finally, we considered four *cycling-event features* to reflect behavioral aspects of bike control. From the binary brake sensor, we extracted the number of braking events (rising edges from 0 to 1) and the ratio of time spent braking relative to the total lap duration. For pedal force, we quantified left–right symmetry (mean and variability of relative imbalance). Summarized in Table 1, this feature set balances general signal descriptors with domain-specific cycling measures.

The resulting vectors capture both short-term dynamics (e.g., pedal stroke oscillations) and higher-level behavioral patterns (e.g., braking frequency, pedal symmetry), providing a rich representation of individual cycling behavior.

4.3 Statistical Analysis

We examined whether features varied between participants using a one-way Kruskal–Wallis test and corrected p-values with the Benjamini–Hochberg false discovery rate (FDR, $\alpha = .05$). Cliff's δ was computed as an effect size. Model performance differences between evaluation conditions (e.g., within-session vs. cross-track) were tested using paired permutation tests (10 000 sign flips) with 95% bootstrap confidence intervals. All tests were non-parametric due to the small sample size and non-normal feature distributions.

4.4 Classification and Evaluation Metrics

Given the limited sample size, we chose the Random Forest (RF) classifier ($n_{estimators}$=200, random_state=42), due to its ability to handle mixed features without scaling, and its robustness to outliers. For evaluation, we performed a traditional approach of within- (same day) and between-sessions for a more profound understanding of the biometric trait performance. As for metrics, we are evaluating the performance in terms of accuracy and F1-score. Default parameters were used without extensive tuning, and overfitting was minimized through leave-one-lap-out cross-validation and strict separation of training and test sessions.

5 Results

We report our findings across three perspectives: (1) within-session performance, where models are trained and tested on repetitions from the same day and track; (2) between-session performance, which evaluates cross-day generalization by training on one session and testing on the other; and (3) subjective feedback on participants' impressions and experiences. This structure allows us to not only establish baseline identification accuracy under controlled conditions, but also to assess robustness across sessions and to contextualize the results with qualitative insights from users.

5.1 Within-Session Performance

We first examined classification performance within the same session, where conditions remained consistent. This serves as a baseline for the feasibility of cycling-based identification under controlled circumstances. First, we evaluated the performance of the short tracks. Across the five repetitions, we performed a 5-fold cross-validation (leave-one-lap-out).

As shown in Table 2, classification accuracies on the short track were consistently high. Using all features, the model reached 94.3% accuracy (F1-score = 0.93) on Day 1 (confusion matrix is seen in Figure 3) and 90.0% (F1-score = 0.88) on Day 2. Comparable results were obtained with sensor-only features (94.3% / 0.93 on Day 1; 95.7% / 0.94 on Day 2) and with sensor+cycling features (92.9% / 0.91 on Day 1; 94.3% / 0.93 on Day 2), suggesting that steering and motion signals carry most of the discriminative power. In contrast, single modalities such as pedal-only (72.9% / 0.68 on Day 1; 64.3% / 0.56 on Day 2), frequency-only (57.1% / 0.51 on Day 1; 51.4% / 0.44 on Day 2), and especially brake-only (5.7% / 0.01 on Day 1; 15.7% / 0.08 on Day 2) provided weak identification performance.

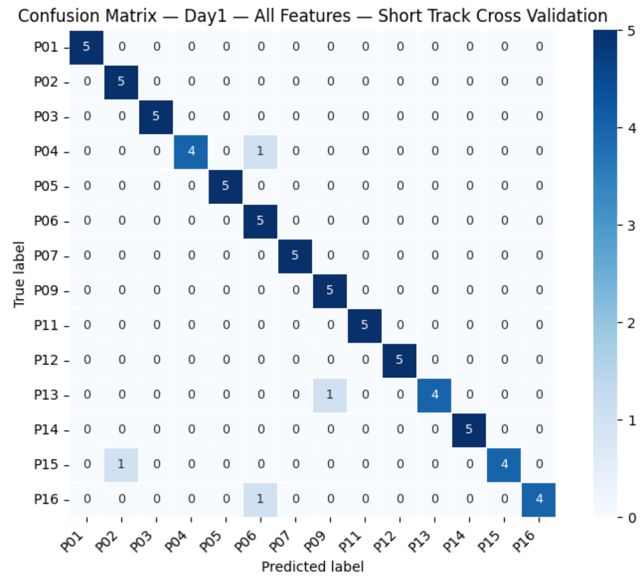


Figure 3: Confusion matrix for Day 1 cross-validation.

When extending to cross-track evaluation within the same day (short⟶long denotes training with short track data and testing with long track values, or vice versa (long⟶short)), accuracies dropped notably. For example, all features achieved 42.9% / 0.33 when transferring from short⟶long, but only 21.4% / 0.14 from long⟶short on Day 1 (42.9% / 0.32 vs. 18.6% / 0.10 on Day 2). This asymmetry indicates that patterns learned on the controlled short track generalize partially to the long track, while the variability of the long track does not transfer back as effectively. Across feature subsets, *sensor+frequency* features showed the highest relative robustness under cross-track conditions (35.7% / 0.27 short⟶long; 24.3% / 0.18 long⟶short on Day 1; 50.0% / 0.41 and 21.4% / 0.14 on Day 2). Together, these results demonstrate that cycling behavior is highly discriminative within a session and that the short track captures more stable and transferable patterns. Additionally, comparing the short and long tracks provides insights into the trade-off between controlled and naturalistic conditions.

Feature Importance. Analysis of feature importance suggested that the most informative features were primarily derived from quaternion signals (capturing steering and orientation), followed by pedaling measures such as symmetry and applied force. Rotation-rate statistics also appeared among the higher-ranked contributors, whereas braking and speed-related measures played only a minor role. Cadence-based features showed limited contribution, indicating that cadence alone may be less distinctive for identifying riders under the current setup. These rankings should, however, be interpreted cautiously, as feature importance can vary with dataset size and model configuration. Future work should investigate which feature groups remain stable across sessions to better understand their long-term discriminative effect.

Table 2: (Accuracy / F1) Results on Day 1 and Day 2. The Results are shown in terms of average cross-validation across the five repetitions of the small track (Short), and between tracks, training with short track laps and testing with the long track lap (Short→Long), and vice versa (Long→Short). Values rounded to three decimals.

Feature Set	Day 1			Day 2		
	Short	Short→Long	Long→Short	Short	Short→Long	Long→Short
All	0.943 / 0.926	0.429 / 0.333	0.214 / 0.143	0.900 / 0.876	0.429 / 0.321	0.186 / 0.099
Sensor only	0.943 / 0.926	0.357 / 0.279	0.257 / 0.205	0.957 / 0.943	0.357 / 0.262	0.243 / 0.163
Frequency only	0.571 / 0.510	0.143 / 0.052	0.071 / 0.016	0.514 / 0.439	0.143 / 0.071	0.071 / 0.010
Sensor + Frequency	0.929 / 0.912	0.357 / 0.274	0.243 / 0.184	0.929 / 0.914	0.500 / 0.410	0.214 / 0.139
Sensor + Cycling	0.929 / 0.912	0.357 / 0.267	0.243 / 0.224	0.943 / 0.926	0.357 / 0.262	0.229 / 0.135
Frequency + Cycling	0.857 / 0.838	0.429 / 0.319	0.171 / 0.113	0.729 / 0.679	0.286 / 0.167	0.171 / 0.087
Cycling (Pedals+Brake)	0.743 / 0.710	0.429 / 0.326	0.300 / 0.226	0.657 / 0.595	0.286 / 0.171	0.229 / 0.170
Pedals only	0.729 / 0.679	0.286 / 0.219	0.314 / 0.228	0.643 / 0.564	0.357 / 0.250	0.171 / 0.085
Brake only	0.057 / 0.009	0.214 / 0.092	0.071 / 0.025	0.157 / 0.081	0.000 / 0.000	0.086 / 0.030

5.2 Between-Session Performance

Next, we assessed performance between sessions, training on day 1 and testing on day 2. This reflects the robustness of cycling behavior over time and under varying environmental conditions. As shown in Table 3, performance decreased notably when models were trained on one session and tested on the other. On the short track, using all features yielded 20.0% accuracy (F1 = 0.11) when training on Day1 and testing on Day2, and 34.3% (F1 = 0.31) in the reverse direction (Day2→Day 1). Sensor-only features performed at a similar level (21.4% / 0.15 and 37.1% / 0.29), while frequency-only and multi-feature combinations, such as frequency+cycling, reached slightly higher values in one direction (e.g., 25.7% / 0.18). However, single modalities like pedals (12.9–34.3%) and brakes (8.6–14.3%) remained close to chance. On the long track, cross-day transfer was even more challenging. With all features, the classifier achieved only 21.4% (F1 = 0.16) for Day1→Day2 and 14.3% (F1 = 0.10) for Day2→Day1. Across subsets, no configuration exceeded 25% accuracy, and brake-only features consistently collapsed to chance level. In summary, these results show that cycling behavior exhibits strong potential as a behavioral biometric within sessions, but faces challenges across sessions. Feature-level analyses reveal that certain signals remain consistently informative, offering directions for minimal sensor setups and more robust designs.

5.3 Subjective Feedback

Participants generally reported positive experiences with the cycling task, as shown in the stacked Likert chart Figure 4. Regarding overall satisfaction, 12 out of 16 participants (75%) rated their experience as mostly or completely satisfying. Comfort ratings were more mixed: 8 participants described the ride as somewhat to very comfortable, while the remainder reported neutral or uncomfortable experiences. In terms of control, pedaling was more frequently described as effortful, with 9 participants rating it as somewhat to very difficult, while only 4 considered it somewhat or very easy. Braking, on the other hand, was consistently perceived as smooth, with 11 participants indicating it was very or extremely easy. Regarding physical effort, responses were balanced, with 6 participants reporting little effort, 6 moderate effort, and 4 high effort, suggesting that while the task was manageable for most, certain sections required significant exertion. Despite these challenges, participants expressed strong interest in the sensor-augmented bicycle concept, with 10 participants indicating they would be somewhat to very interested in acquiring such a bike.

When asked to indicate if any specific sections of the cycling tracks caused discomfort, fatigue, or other issues, participants reported minimal problems on the shorter route. Fourteen participants explicitly noted "No issues", with only two reporting difficulties in Section 7 (e.g., "*There was a bump on the ground to protect cables*", (P3, M, 31y)). In contrast, participants identified multiple problematic areas within the longer route. Section 12 (9 mentions) and Section 5 (8 mentions) emerged as the most frequently reported problem areas, largely due to the slope present in this part of the track. Participants emphasized the challenge of cycling uphill and downhill, for example: "*It was difficult to cycle uphill without standing on the bike*" (P2, M, 23y) and "*In Section 12 there was a slope which made it almost impossible to ride the bike.*" (P4, M, 23y). Additional reports concerned Sections 2, 1, 4, 13, 14, and 3, though these appeared less frequently (1–4 mentions each). As illustrated in the maps shown in Figure 2(b), these labels correspond to specific points along the track where physical or ergonomic challenges were concentrated. Such exertions are important to acknowledge, as they may have influenced participants' cycling behavior. For future biometric analyses, these segments may warrant special consideration or exclusion to ensure more consistent and reliable behavioral assessment.

6 Discussion

This work represents an exploratory first step towards establishing cycling as a behavioral biometric. While the results are promising, we emphasize that this work is an early investigation designed to scope feasibility and to motivate larger-scale, more diverse studies in the future.

Table 3: Between-session performance (Accuracy / F1). Models trained on Day 1 and tested on Day 2, and vice versa, on short and long tracks.

Feature Set	Short Day1→Day2	Short Day2→Day1	Long Day1→Day2	Long Day2→Day1
All (F0)	0.200 / 0.108	0.343 / 0.306	0.429 / 0.342	0.357 / 0.238
Sensor only	0.214 / 0.153	0.171 / 0.148	0.143 / 0.071	0.071 / 0.048
Frequency only	0.243 / 0.202	0.300 / 0.228	0.071 / 0.036	0.214 / 0.179
Sensor+Frequency	0.200 / 0.120	0.243 / 0.225	0.286 / 0.202	0.214 / 0.143
Sensor+Cycling	0.200 / 0.108	0.343 / 0.306	0.429 / 0.342	0.357 / 0.238
Frequency+Cycling	0.257 / 0.181	0.214 / 0.196	0.214 / 0.112	0.214 / 0.143
Cycling (Pedals+Brake)	0.157 / 0.126	0.200 / 0.162	0.214 / 0.143	0.286 / 0.214
Pedals only	0.129 / 0.100	0.171 / 0.120	0.143 / 0.095	0.143 / 0.064
Brake only	0.086 / 0.026	0.100 / 0.044	0.143 / 0.064	0.071 / 0.029

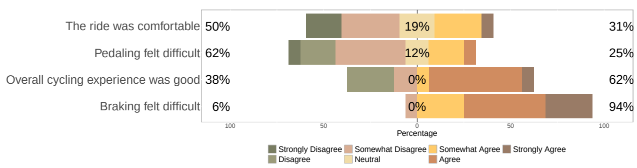


Figure 4: Subjective feedback for the quantitative questions. The ranges are highlighted.

6.1 The Potential of Cycling as a Biometric Trait

In this work, we investigated our primary research question (**RQ1**): *To what extent can cycling be used as a behavioral biometric for continuous and implicit user identification?* To address this, we conducted an empirical study by instrumenting a conventional bicycle with sensors on the pedals, brake, and frame to capture cycling dynamics. Our results demonstrate the potential of cycling as a distinctive behavioral trait, with within-session identification accuracies reaching up to 94.3%. At the same time, transferring models from the controlled short track to the long, uncontrolled track led to a clear drop in accuracy (42.9%). This degradation is likely due to additional sources of variability in the in-situ track (e.g., road slopes, unexpected stops, or traffic interactions) that were absent from the controlled setup and differed across sessions.

Behavioral Drift. Like most behavioral biometrics, cycling is subject to *behavioral drift*, i.e., performance decline across sessions [23]. Interestingly, we did not observe a consistent decrease when training and testing on the same track type (short-to-short or long-to-long across days), suggesting that core aspects of cycling behavior remain relatively stable over time. This strengthens the case for cycling as a feasible behavioral identifier. We anticipate that continuous data collection, together with awareness of contextual factors (e.g., environment, physical state, or riding purpose), could mitigate drift effects and ultimately improve identification robustness in real-world deployment.

Despite between-session variability, continuously capturing and updating cycling profiles could yield increased accuracy and more robust performance. Adopting cycling as a biometric trait opens the door to personalized adjustments for the rider (e.g., saddle height, preferred route recommendations), which may not only improve comfort but also enhance the overall cycling experience. Beyond personalization, more critical use cases are conceivable: with continuous training and context-awareness, the bicycle could unobtrusively verify its rider's identity, enabling anti-theft applications that provide continuous protection without additional effort from the user.

6.2 Cycling Components' Impact on Identification

Our second research question (**RQ2**) asked: *Which behavioral features contribute most to identification accuracy, and how can this knowledge guide the design of minimal and practical sensor configurations for real-world deployment?* Our feature importance analysis revealed that steering and orientation dynamics, captured through quaternion-based measures, consistently dominated across sessions. Pedaling-related measures, particularly symmetry and pedal weight distribution, provided complementary cues that further enhanced user separability. By contrast, braking and cadence-based measures contributed relatively little, likely because braking occurs infrequently and cadence signals were less distinctive across individuals.

These findings have direct implications for practical deployment. They suggest that reliable identification can be achieved with a minimal sensor setup consisting of motion sensors mounted on the bicycle frame or handlebars, combined with pedal force sensors. In contrast, additional instrumentation such as brake sensors or cadence monitors may not be necessary, simplifying system design and lowering deployment cost. Importantly, this also means that identification relies on signals already generated during natural riding, without requiring riders to change their behavior.

6.3 Potential Use Cases

Understanding a rider's identity through cycling behavior opens several promising application areas. The first is *personalization*.

If a bicycle can implicitly recognize its rider, it could automatically adjust to individual preferences, such as suggesting preferred routes to regular destinations or, in the case of electric bicycles, adapting motor assistance based on previously observed riding patterns. A second use case is *security*. Continuous identification enables behavioral biometric locks that complement or even replace traditional mechanical locks. Unlike one-time authentication mechanisms, such a system could continuously verify that the bicycle is used by its legitimate owner, providing unobtrusive and ongoing protection against theft. We note, however, that this approach may limit a bicycle to a single registered rider unless multi-user models are explicitly considered. Beyond individual use, cycling biometrics could also support *group dynamics*. In scenarios where multiple bicycles are equipped with sensors, rider identities and behaviors could be shared within the group to coordinate collective activities (e.g., monitoring group cohesion, adapting assistance to maintain pace, or providing safety alerts). Together, these examples highlight the breadth of opportunities for cyclist-aware systems that go beyond identification to personalization, safety, and coordination.

6.4 Limitations and Future Work

Despite the thorough investigation, several limitations must be acknowledged. The study was conducted with a limited number of participants across only two sessions, which limits the ability to examine long-term stability (i.e., the behavioral drift) and generalize across larger populations. In addition, while participants naturally varied in their clothing and footwear, we did not systematically investigate the effect of such factors on identification performance. Finally, our setup employed a specific sensor configuration on a single conventional bicycle, which may limit generalizability to other bicycle types or sensor placements.

Future research should expand this investigation by recruiting a larger and more diverse participants and by conducting studies across varying cycling environments. Longitudinal deployments with longer temporal gaps between sessions are needed to assess the long-term stability of cycling biometrics, and to develop normalization or adaptation strategies that mitigate session-to-session variability. Systematic investigations of clothing, footwear, and environmental conditions would provide a deeper understanding of their impact on performance. Ultimately, in-the-wild long-term deployments will be essential to evaluate the scalability of cycling biometrics for real-world applications in personalization, safety, and security.

7 Conclusion

In this paper, we presented an exploratory study investigating cycling as a behavioral biometric. By equipping a conventional bicycle with unobtrusive sensors and evaluating rider identification across controlled and in-the-wild tracks, we demonstrated that cycling dynamics can serve as distinctive behavioral signatures. Our results showed strong within-session performance, confirming the feasibility of this approach, while also revealing challenges such as performance drops in cross-track and cross-session evaluations. Feature analyses further indicated that steering and pedaling dynamics contribute most to identification accuracy, pointing toward minimal and practical sensor configurations for real-world deployment. These findings establish cycling as a promising behavioral biometric trait that can support both personalization and security applications. While our study was limited in scale, it offers a valuable first step toward scalable, in-the-wild deployments of cycling biometrics. Future work should expand to larger participant groups, varied environments, and longer time spans to better understand stability, ecological robustness, and user acceptance. By highlighting both opportunities and challenges, this work provides a foundation for developing rider-aware bicycles that adapt to their users, protect against misuse, and enrich the cycling experience.

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References

[1] Yasmeen Abdrabou, Lukas Mecke, Radiah Rivu, Sarah Prange, Quy Dat Nguyen, Vanessa Voigt, Florian Alt, and Ken Pfeuffer. 2023. How Unique do we Move? Understanding the Human Body and Context Factors for User Identification. In *Proceedings of Mensch und Computer 2023*. 127–137.

[2] Mohammed Abuhamad, Ahmed Abusnaina, DaeHun Nyang, and David Mohaisen. 2020. Sensor-based continuous authentication of smartphones' users using behavioral biometrics: A contemporary survey. *IEEE Internet of Things Journal* 8, 1 (2020), 65–84.

[3] Maedeh Agharazidermani, Lincoln Lu, and Kristy Elizabeth Boyer. 2023. Exploring Real-Time Collaborative Heart Rate Displays for Cycling Partners. In *Proceedings of the 25th International Conference on Mobile Human-Computer Interaction* (Athens, Greece) *(MobileHCI '23 Companion)*. Association for Computing Machinery, New York, NY, USA, Article 7, 7 pages. doi:10.1145/3565066.3608692

[4] Rajwa Al-Hrathi, Ali Karime, Hussein Al-Osman, and Abdulmotaleb El Saddik. 2012. Exerlearn Bike: An Exergaming System for Children's Educational and Physical Well-Being. In *2012 IEEE International Conference on Multimedia and Expo Workshops*. 489–494. doi:10.1109/ICMEW.2012.91

[5] Robert Albrecht, Riitta Väänänen, and Tapio Lokki. 2016. Guided by music: pedestrian and cyclist navigation with route and beacon guidance. *Personal and Ubiquitous Computing* 20 (2016), 121–145. doi:10.1007/s00779-016-0906-z

[6] Josh Andres, Julian de Hoog, and Florian 'Floyd' Mueller. 2018. "I had superpowers when eBike riding" Towards Understanding the Design of Integrated Exertion. In *Proceedings of the 2018 Annual Symposium on Computer-Human Interaction in Play (CHI PLAY '18)*. Association for Computing Machinery, New York, NY, USA, 19–31. doi:10.1145/3242671.3242688

[7] Josh Andres, Tuomas Kari, Juerg von Kaenel, and Florian 'Floyd' Mueller. 2019. "Co-riding With My eBike to Get Green Lights". In *Proceedings of the 2019 on Designing Interactive Systems Conference (DIS '19)*. Association for Computing Machinery, New York, NY, USA, 1251–1263. doi:10.1145/3322276.3322307

[8] Josh Andres, m.c. schraefel, Nathan Semertzidis, Brahmi Dwivedi, Yutika C. Kulwe, Juerg von Kaenel, and Florian Floyd Mueller. 2020. Introducing Peripheral Awareness as a Neurological State for Human-computer Integration. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. doi:10.1145/3313831.3376128

[9] Marit Bentvelzen, Gian-Luca Savino, Jasmin Niess, Judith Masthoff, and Paweł W. Wozniak. 2022. Tailor My Zwift: How to Design for Amateur Sports in the Virtual World. *Proc. ACM Hum.-Comput. Interact.* 6, MHCI, Article 216 (sep 2022), 23 pages. doi:10.1145/3546751

[10] Alexander Bigazzi, Fajar Ausri, Luke Peddie, Dillon Fitch, and Eli Puterman. 2022. Physiological markers of traffic-related stress during active travel. *Transportation Research Part F: Traffic Psychology and Behaviour* 84 (2022), 223–238. doi:10.1016/j.trf.2021.12.003

[11] Martyna Bogacz, Stephane Hess, Charisma F. Choudhury, Chiara Calastri, Faisal Mushtaq, Muhammad Awais, Mohsen Nazemi, Michael AB van Eggermond, and Alexander Erath. 2021. Cycling in virtual reality: modelling behaviour in an immersive environment. *Transportation letters* 13, 8 (2021), 608–622.

[12] Mario Boot, Laura Kahnt, Dees Postma, Mehmet Baran Ulak, Karst Geurs, and Paul Havinga. 2024. Are We in Flow? Measuring and Supporting Simultaneous Flow in

Duos of Elderly Cyclists. In *2024 IEEE International Conference on Pervasive Computing and Communications Workshops and other Affiliated Events (PerCom Workshops)*. IEEE, New York, NY, USA, 255–260. doi:10.1109/PerComWorkshops59983.2024.10503119

[13] Mario Boot, Mehmet Baran Ulak, Karst T. Geurs, and Paul J. M. Havinga. 2024. Using body sensors for evaluating the impact of smart cycling technologies on cycling experiences: a systematic literature review and conceptual framework. *European Transport Research Review* 16, 1 (14 Feb 2024), 13. doi:10.1186/s12544-024-00635-3

[14] Catia Cepeda, Joao Rodrigues, Maria Camila Dias, Diogo Oliveira, Dina Rindlisbacher, Marcus Cheetham, and Hugo Gamboa. 2018. Mouse tracking measures and movement patterns with application for online surveys. In *International Cross-Domain Conference for Machine Learning and Knowledge Extraction*. Springer, 28–42.

[15] Amanpreet Chander, Abhinav Airan, and Ashish Sahani. 2023. A virtual reality based system for a more engaging indoor exercise biking experience. In *2023 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*. 01–06. doi:10.1109/I2MTC53148.2023.10176061

[16] Sromona Chatterjee, Kevin Scheck, Dennis Küster, Felix Putze, Harish Moturu, Johannes Schering, Jorge Marx Gómez, and Tanja Schultz. 2021. SmartHelm: Towards Multimodal Detection of Attention in an Outdoor Augmented Reality Biking Scenario. In *Companion Publication of the 2020 International Conference on Multimodal Interaction* (Virtual Event, Netherlands) *(ICMI '20 Companion)*. Association for Computing Machinery, New York, NY, USA, 426–432. doi:10.1145/3395035.3425207

[17] Manuel Chavarrias, Jorge Carlos-Vivas, Daniel Collado-Mateo, and Jorge Pérez-Gómez. 2019. Health Benefits of Indoor Cycling: A Systematic Review. *Medicina* 55, 8 (2019). doi:10.3390/medicina55080452

[18] Natalia Chukhlantseva. 2019. Effectiveness of an indoor cycling program in improving the physical condition of young women. *Polish Journal of Sport and Tourism* 26, 3 (2019), 14–19.

[19] Alexandru Dancu, Velko Vechev, Adviye Ayça Ünlüer, Simon Nilson, Oscar Nygren, Simon Eliasson, Jean-Elie Barjonet, Joe Marshall, and Morten Fjeld. 2015. Gesture Bike: Examining Projection Surfaces and Turn Signal Systems for Urban Cycling. In *Proceedings of the 2015 International Conference on Interactive Tabletops & Surfaces* (Madeira, Portugal) *(ITS '15)*. Association for Computing Machinery, New York, NY, USA, 151–159. doi:10.1145/2817721.2817748

[20] Daniel H. De La Iglesia, Juan F. De Paz, Gabriel Villarrubia González, Alberto L. Barriuso, Javier Bajo, and Juan M. Corchado. 2018. Increasing the Intensity over Time of an Electric-Assist Bike Based on the User and Route: The Bike Becomes the Gym. *Sensors* 18, 1 (2018), 21. doi:10.3390/s18010220

[21] Tian-Ming Deng, Jing-hou Fu, Yi-Ming Shao, Jin-shuan Peng, and Jin Xu. 2019. Pedal operation characteristics and driving workload on slopes of mountainous road based on naturalistic driving tests. *Safety Science* 119 (2019), 40–49.

[22] Marco Dozza and Julia Werneke. 2014. Introducing naturalistic cycling data: What factors influence bicyclists' safety in the real world? *Transportation research part F: traffic psychology and behaviour* 24 (2014), 83–91.

[23] Simon Eberz, Kasper B Rasmussen, Vincent Lenders, and Ivan Martinovic. 2017. Evaluating behavioral biometrics for continuous authentication: Challenges and metrics. In *Proceedings of the 2017 ACM on Asia conference on computer and communications security*. 386–399.

[24] Juliano Franz and Derek Reilly. 2022. Ride With Me: Exploring Group Road Cycling Through Contextual Design. In *Proceedings of the 2022 ACM Designing Interactive Systems Conference (DIS '22)*. Association for Computing Machinery, New York, NY, USA, 1612–1625. doi:10.1145/3532106.3533476

[25] Karim Habib, Lisa L Losada-Rojas, and Nicholas N Ferenchak. 2024. Review of the Impacts of Human Factors on Cycling: Perceptions, Workload, and Behavior. *Transportation Research Record* (2024), 03611981241242766.

[26] R. Herpers, W. Heiden, M. Kutz, D. Scherfgen, U. Hartmann, J. Bongartz, and O. Schulzyk. 2008. FIVIS Bicycle Simulator: An Immersive Game Platform for Physical Activities. In *Proceedings of the 2008 Conference on Future Play: Research, Play, Share* (Toronto, Ontario, Canada) *(Future Play '08)*. Association for Computing Machinery, New York, NY, USA, 244–247. doi:10.1145/1496984.1497035

[27] Emil Rosenlund Høeg, Jon Ram Bruun-Pedersen, Shannon Cheary, Lars Koreska Andersen, Razvan Paisa, Stefania Serafin, and Belinda Lange. 2023. Buddy biking: a user study on social collaboration in a virtual reality exergame for rehabilitation. *Virtual Reality* 27, 1 (2023), 245–262.

[28] Ching-Ting Hsu, Yang-Hung Chang, J Chen, W Ho, H Lin, and J Chou. 2020. Implementation of Internet of Public Fitness Equipment for Health Physical Fitness Improvement. *WSEAS Trans. Comput. Res* 8 (2020), 16–20.

[29] Anil Jain, Lin Hong, and Sharath Pankanti. 2000. Biometric identification. *Commun. ACM* 43, 2 (2000), 90–98.

[30] Anil K Jain, Debayan Deb, and Joshua J Engelsma. 2021. Biometrics: Trust, but verify. *IEEE Transactions on Biometrics, Behavior, and Identity Science* 4, 3 (2021), 303–323.

[31] Sung Hwan Jeong, Yong Jun Piao, Woo Suk Chong, Yong Yook Kim, Sang Min Lee, Tae Kyu Kwon, Chul Un Hong, and Nam Gyun Kim. 2005. The Development of a New Training System for Improving Equilibrium Sense Using a Virtual Bicycle Simulator. In *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*. IEEE, New York, NY, USA, 2567–2570. doi:10.1109/IEMBS.2005.1616993

[32] Eric M. Jones, Ted Selker, and Hyemin Chung. 2007. What You Said about Where You Shook Your Head: A Hands-Free Implementation of a Location-Based Notification System. In *CHI '07 Extended Abstracts on Human Factors in Computing Systems* (San Jose, CA, USA) *(CHI EA '07)*. Association for Computing Machinery, New York, NY, USA, 2477–2482. doi:10.1145/1240866.1241027

[33] Thomas Karanikiotis, Michail D Papamichail, Kyriakos C Chatzidimitriou, Napoleon-Christos I Oikonomou, Andreas L Symeonidis, and Sashi K Saripalle. 2020. Continuous implicit authentication through touch traces modelling. In *2020 IEEE 20th International conference on software quality, reliability and security (QRS)*. IEEE, 111–120.

[34] Tohru Kiryu and H. Minagawa. 2013. Feasibility study on a perceived fatigue prediction dependent power control for an electrically assisted bicycle. In *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, New York, NY, USA, 2088–2091. doi:10.1109/EMBC.2013.6609944

[35] Sarah Martina Kolly, Roger Wattenhofer, and Samuel Welten. 2012. A personal touch: Recognizing users based on touch screen behavior. In *Proceedings of the third international workshop on sensing applications on mobile phones*. 1–5.

[36] Yassin Kortli, Maher Jridi, Ayman Al Falou, and Mohamed Atri. 2020. Face recognition systems: A survey. *Sensors* 20, 2 (2020), 342.

[37] Thomas Kosch, Andrii Matviienko, Florian Müller, Jessica Bersch, Christopher Katins, Dominik Schön, and Max Mühlhäuser. 2022. NotiBike: Assessing Target Selection Techniques for Cyclist Notifications in Augmented Reality. *Proc. ACM Hum.-Comput. Interact.* 6, MHCI, Article 197 (sep 2022), 24 pages. doi:10.1145/3546732

[38] Andraž Krašovec, Daniel Pellarini, Dimitrios Geneiatakis, Gianmarco Baldini, and Veljko Pejović. 2020. Not quite yourself today: Behaviour-based continuous authentication in IoT environments. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 4, 4 (2020), 1–29.

[39] Jonathan Liebers, Christian Burschik, Uwe Gruenefeld, and Stefan Schneegass. 2023. Exploring the stability of behavioral biometrics in virtual reality in a remote field study: Towards implicit and continuous user identification through body movements. In *Proceedings of the 29th ACM Symposium on Virtual Reality Software and Technology*. 1–12.

[40] Tommy Lim, Anjani Kalra, Jason Thompson, Joanne Caldwell Odgers, and Ben Beck. 2022. Physiological measures of bicyclists' subjective experiences: A scoping review. *Transportation Research Part F: Traffic Psychology and Behaviour* 90 (2022), 365–381. doi:10.1016/j.trf.2022.09.007

[41] Andrii Matviienko, Swamy Ananthanarayan, Shadan Sadeghian Borojeni, Yannick Feld, Wilko Heuten, and Susanne Boll. 2018. Augmenting Bicycles and Helmets with Multimodal Warnings for Children. In *Proceedings of the 20th International Conference on Human-Computer Interaction with Mobile Devices and Services* (Barcelona, Spain) *(MobileHCI '18)*. Association for Computing Machinery, New York, NY, USA, Article 15, 13 pages. doi:10.1145/3229434.3229479

[42] Andrii Matviienko, Swamy Ananthanarayan, Abdallah El Ali, Wilko Heuten, and Susanne Boll. 2019. NaviBike: Comparing Unimodal Navigation Cues for Child Cyclists. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. doi:10.1145/3290605.3300850

[43] Andrii Matviienko, Swamy Ananthanarayan, Raphael Kappes, Wilko Heuten, and Susanne Boll. 2020. Reminding Child Cyclists about Safety Gestures. In *Proceedings of the 9TH ACM International Symposium on Pervasive Displays* (Manchester, United Kingdom) *(PerDis '20)*. Association for Computing Machinery, New York, NY, USA, 1–7. doi:10.1145/3393712.3394120

[44] Andrii Matviienko, Josh Andres, and Florian 'Floyd' Mueller. 2024. Grand challenges in CyclingHCI. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference* (IT University of Copenhagen, Denmark) *(DIS '24)*. Association for Computing Machinery, New York, NY, USA, 2577–2590. doi:10.1145/3643834.3661550

[45] Andrii Matviienko, Florian Heller, and Bastian Pfleging. 2021. Quantified Cycling Safety: Towards a Mobile Sensing Platform to Understand Perceived Safety of Cyclists. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI EA '21)*. Association for Computing Machinery, New York, NY, USA, Article 262, 6 pages. doi:10.1145/3411763.3451678

[46] Andrii Matviienko, Hajris Hoxha, and Max Mühlhäuser. 2023. What does it mean to cycle in Virtual Reality? Exploring Cycling Fidelity and Control of VR Bicycle Simulators. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 879, 15 pages. doi:10.1145/3544548.3581050

[47] Andrii Matviienko, Manuel Lehé, Florian Heller, Bastian Pfleging, and Max Mühlhäuser. 2023. QuantiBike: Quantifying Perceived Cyclists' Safety via Head Movements in Virtual Reality and Outdoors. In *Proceedings of the 2023 ACM Symposium on Spatial User Interaction (SUI '23)*. Association for Computing Machinery, New York, NY, USA, Article 27, 12 pages. doi:10.1145/3607822.3614532

[48] Andrii Matviienko, Damir Mehmedovic, Florian Müller, and Max Mühlhäuser. 2022. "Baby, You can Ride my Bike": Exploring Maneuver Indications of Self-Driving Bicycles using a Tandem Simulator *(MobileHCI '22)*. Association for Computing Machinery, New York, NY, USA. doi:10.1145/3546723

[49] Andrii Matviienko, Florian Müller, Dominik Schön, Paul Seesemann, Sebastian Günther, and Max Mühlhäuser. 2022. BikeAR: Understanding Cyclists' Crossing Decision-Making at Uncontrolled Intersections using Augmented Reality. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 366, 15 pages. doi:10.1145/3491102.3517560

[50] Andrii Matviienko, Florian Müller, Marcel Zickler, Lisa Alina Gasche, Julia Abels, Till Steinert, and Max Mühlhäuser. 2022. Reducing Virtual Reality Sickness for Cyclists in VR Bicycle Simulators. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 187, 14 pages. doi:10.1145/3491102.3501959

[51] Alexander Michael and Christof Lutteroth. 2020. Race Yourselves: A Longitudinal Exploration of Self-Competition Between Past, Present, and Future Performances in a VR Exergame. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–17. doi:10.1145/3313831.3376256

[52] Kien Nguyen, Hugo Proença, and Fernando Alonso-Fernandez. 2024. Deep learning for iris recognition: A survey. *Comput. Surveys* 56, 9 (2024), 1–35.

[53] Franklin Oliveira, Dilan Nery, Daniel G Costa, Ivanovitch Silva, and Luciana Lima. 2021. A survey of technologies and recent developments for sustainable smart cycling. *Sustainability* 13, 6 (2021), 3422.

[54] Martin Pielot, Benjamin Poppinga, Wilko Heuten, and Susanne Boll. 2012. Tacticycle: Supporting Exploratory Bicycle Trips. In *Proceedings of the 14th International Conference on Human-Computer Interaction with Mobile Devices and Services* (San Francisco, California, USA) *(MobileHCI '12)*. Association for Computing Machinery, New York, NY, USA, 369–378. doi:10.1145/2371574.2371631

[55] Gang Ren, Zhihuang Huang, Wenshuo Lin, Ning Miao, Tianyang Huang, Gang Wang, and Jee-Hang Lee. 2025. Multimodal Guidance for Enhancing Cyclist Road Awareness. *Electronics* 14, 7 (2025), 1363.

[56] Duncan Rowland, Martin Flintham, Leif Oppermann, Joe Marshall, Alan Chamberlain, Boriana Koleva, Steve Benford, and Citlali Perez. 2009. Ubikequitous Computing: Designing Interactive Experiences for Cyclists. In *Proceedings of the 11th International Conference on Human-Computer Interaction with Mobile Devices and Services* (Bonn, Germany) *(MobileHCI '09)*. Association for Computing Machinery, New York, NY, USA, Article 21, 11 pages. doi:10.1145/1613858.1613886

[57] Vasin Ruengjittaveekul and Marong Phadoongsidhi. 2020. Fitness Activity Acquisition and Communication Interface for Running Treadmill. In *2020 17th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*. 335–340. doi:10.1109/ECTI-CON49241.2020.9158087

[58] Riseul Ryu, Soonja Yeom, David Herbert, and Julian Dermoudy. 2023. A comprehensive survey of context-aware continuous implicit authentication in online learning environments. *IEEE Access* 11 (2023), 24561–24573.

[59] Baljit Singh Saini, Navdeep Kaur, and Kamaljit Singh Bhatia. 2016. Keystroke dynamics for mobile phones: A survey. *Indian Journal of Science and Technology* 9, 6 (2016), 1–8.

[60] Philip Schmidt, Attila Reiss, Robert Dürichen, and Kristof Van Laerhoven. 2019. Wearable-Based Affect Recognition—A Review. *Sensors* 19, 19 (2019), 42. doi:10.3390/s19194079

[61] Eldon Schoop, James Smith, and Bjoern Hartmann. 2018. HindSight: Enhancing Spatial Awareness by Sonifying Detected Objects in Real-Time 360-Degree Video. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–12. doi:10.1145/3173574.3173717

[62] Haska Steltenpohl and Anders Bouwer. 2013. Vibrobelt: Tactile Navigation Support for Cyclists. In *Proceedings of the 2013 International Conference on Intelligent User Interfaces* (Santa Monica, California, USA) *(IUI '13)*. Association for Computing Machinery, New York, NY, USA, 417–426. doi:10.1145/2449396.2449450

[63] Giuseppe Stragapede, Ruben Vera-Rodriguez, Ruben Tolosana, and Aythami Morales. 2023. BehavePassDB: public database for mobile behavioral biometrics and benchmark evaluation. *Pattern Recognition* 134 (2023), 109089.

[64] Debra A Stroiney, John D Ranney, and Navid Ghodddosi. 2019. Exercise Intensity as a Predictor of Mood States During a Group Cycling Class: 2608 Board# 272 May 31 9:30AM-11:00AM. *Medicine & Science in Sports & Exercise* 51, 6S (2019), 727. https://journals.lww.com/acsm-msse/fulltext/2019/06001/exercise_intensity_as_a_predictor_of_mood_states.2177.aspx

[65] Ioannis C Stylios, Olga Thanou, Iosif Androulidakis, and Elena Zaitseva. 2016. A review of continuous authentication using behavioral biometrics. In *Proceedings of the SouthEast European Design Automation, Computer Engineering, Computer Networks and Social Media Conference*. 72–79.

[66] Danilo Valdes-Ramirez, Miguel Angel Medina-Pérez, Raúl Monroy, Octavio Loyola-González, Jorge Rodríguez-Ruiz, Aythami Morales, and Francisco Herrera. 2019. A Review of Fingerprint Feature Representations and Their Applications for Latent Fingerprint Identification: Trends and Evaluation. *IEEE Access* 7, 1 (2019), 48484–48499.

[67] Archana Venkatachalapathy, Cara Hamann, Steven Spears, Elizabeth A. Shirtcliff, and Anuj Sharma. 2022. A naturalistic study assessing the impact of daytime running lights and vehicle passing events on cyclist's physiological stress. *Transportation Research Interdisciplinary Perspectives* 16 (2022), 100703. doi:10.1016/j.trip.2022.100703

[68] Tamara von Sawitzky, Thomas Grauschopf, and Andreas Riener. 2022. “Attention! A Door Could Open.”—Introducing Awareness Messages for Cyclists to Safely Evade Potential Hazards. *Multimodal Technologies and Interaction* 6, 1 (2022). doi:10.3390/mti6010003

[69] Wouter Walmink, Alan Chatham, and Florian Mueller. 2014. Interaction Opportunities around Helmet Design. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems* (Toronto, Ontario, Canada) *(CHI EA '14)*. Association for Computing Machinery, New York, NY, USA, 367–370. doi:10.1145/2559206.2574803

[70] Wouter Walmink, Danielle Wilde, and Florian 'Floyd' Mueller. 2014. Displaying Heart Rate Data on a Bicycle Helmet to Support Social Exertion Experiences. In *Proceedings of the 8th International Conference on Tangible, Embedded and Embodied Interaction* (Munich, Germany) *(TEI '14)*. Association for Computing Machinery, New York, NY, USA, 97–104. doi:10.1145/2540930.2540970

[71] Changsheng Wan, Li Wang, and Vir V Phoha. 2018. A survey on gait recognition. *ACM Computing Surveys (CSUR)* 51, 5 (2018), 1–35.

[72] Renzhong Wang and Dan Tao. 2019. Context-aware implicit authentication of smartphone users based on multi-sensor behavior. *IEEE Access* 7 (2019), 119654–119667.

[73] Darren ER Warburton, Shannon SD Bredin, Leslie TL Horita, Dominik Zbogar, Jessica M Scott, Ben TA Esch, and Ryan E Rhodes. 2007. The health benefits of interactive video game exercise. *Applied Physiology, Nutrition, and Metabolism* 32, 4 (2007), 655–663.

[74] Darren ER Warburton, Crystal Whitney Nicol, and Shannon SD Bredin. 2006. Health benefits of physical activity: the evidence. *Cmaj* 174, 6 (2006), 801–809.

[75] Philipp Wintersberger, Andrii Matviienko, Andreas Schweidler, and Florian Michahelles. 2022. Development and Evaluation of a Motion-based VR Bicycle Simulator. *Proc. ACM Hum.-Comput. Interact.* 6, MHCI, Article 210 (sep 2022), 19 pages. doi:10.1145/3546745

[76] Philipp Wintersberger, Ambika Shahu, Johanna Reisinger, Fatemeh Alizadeh, and Florian Michahelles. 2022. Self-Balancing Bicycles: Qualitative Assessment and Gaze Behavior Evaluation. In *Proceedings of the 21st International Conference on Mobile and Ubiquitous Multimedia* (Lisbon, Portugal) *(MUM '22)*. Association for Computing Machinery, New York, NY, USA, 189–199. doi:10.1145/3568444.3568451

[77] Cong Wu, Kun He, Jing Chen, and Ruiying Du. 2019. ICAuth: Implicit and continuous authentication when the screen is awake. In *ICC 2019-2019 IEEE International Conference on Communications (ICC)*. IEEE, 1–6.

[78] Yi Wu, Luis Alonso González Villalobos, Zhenning Yang, Gregory Thomas Croisdale, Çağdaş Karataş, and Jian Liu. 2023. SmarCyPad: A Smart Seat Pad for Cycling Fitness Tracking Leveraging Low-cost Conductive Fabric Sensors. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 7, 3, Article 135 (sep 2023), 26 pages. doi:10.1145/3610927

[79] Godwin Yeboah, Seraphim Alvanides, and Emine Mine Thompson. 2014. Everyday cycling in urban environments: Understanding behaviors and constraints in space-time. In *Computational approaches for urban environments*. Springer, 185–210.

[80] Wenyi Zhao, Rama Chellappa, P Jonathon Phillips, and Azriel Rosenfeld. 2003. Face recognition: A literature survey. *ACM computing surveys (CSUR)* 35, 4 (2003), 399–458.

[81] Yu Zhong and Yunbin Deng. 2015. A survey on keystroke dynamics biometrics: approaches, advances, and evaluations. In *Recent Advances in User Authentication Using Keystroke Dynamics Biometrics*. Number 1. Science Gate Publishing, 1–22.