

Gamification and Social Interaction in Music-Synchronized Group Cycling with Heart-Rate- and Cadence-Based Feedback

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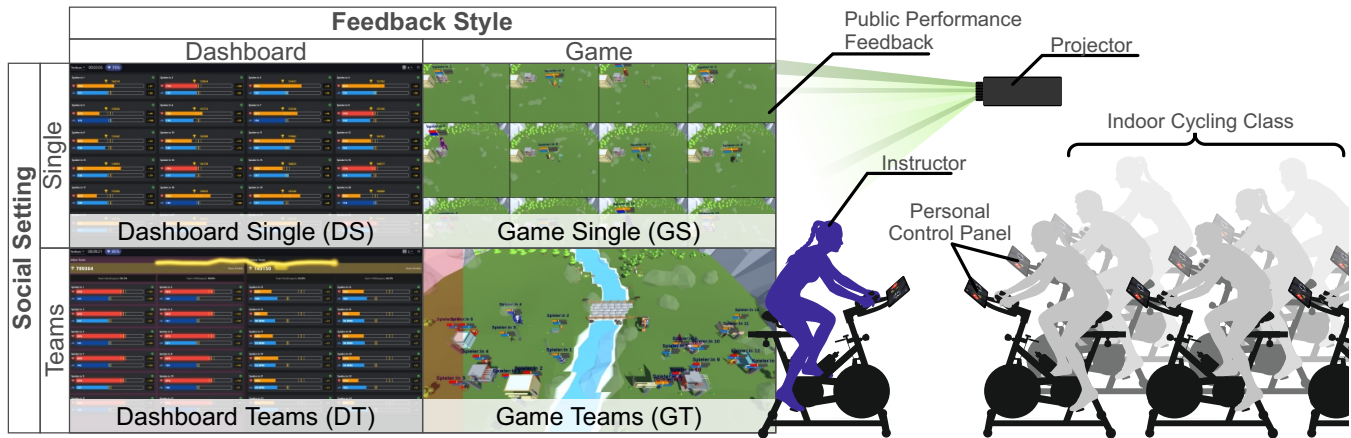


Figure 1: Overview of the study setup and 2x2 design. In instructor-led indoor cycling classes, participants ride sensor-enhanced bikes with tablets displaying a private Personal Control Panel, while a projector shows Public Performance Feedback next to the instructor on the wall, allowing cyclists to view class data during training. The study varied Feedback Style and Social Setting, resulting in four conditions: Dashboard Single (DS), Dashboard Teams (DT), Game Single (GS), and Game Teams (GT).

Abstract

Indoor cycling classes use music, instructor feedback, and group dynamics, yet current systems provide limited support for richer gamification and social training mechanics. We investigated how gamification and social interaction shape user experience and synchronization in sensor-based, music-synchronized group cycling. We implemented four conditions in a 2x2 design varying feedback style (Dashboard vs. Game) and social setting (Single vs. Teams). In a within-subjects field study in real classes ($N = 61$; counterbalanced

analysis on a subgroup $n = 44$), the strongest effects emerged between Dashboard and Game conditions. Dashboards were perceived as more pragmatic and less mentally demanding, and supported higher flow and better subjective and objective cadence synchronization. Games showed stronger hedonic qualities, whereas Team modes primarily increased perceived beat synchronization. These findings position combined heart-rate- and cadence-based feedback as a promising design resource for group exercise, while suggesting that suitable gamification and social mechanics depend on context, experience, and individual preferences.



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CCS Concepts

• **Human-centered computing** → **Human computer interaction (HCI)**; **Field studies**; **Empirical studies in HCI**; **Interactive systems and tools**; **Collaborative and social computing**; **Collaborative interaction**; • **Applied computing** → **Sound and music computing**; **Consumer health**; **Health informatics**.

Keywords

Indoor Cycling, Spinning®, SportsHCI, Group Exercise, Music, Gamification, Social Interaction, Field Study, Motivation, Flow, Synchronization, Heart Rate, Cadence

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1 Introduction

Unhealthy lifestyles, characterized by sedentary routines, poor diet, and insufficient physical activity, remain a major societal challenge [72, 87]. Regular exercise is therefore essential, and indoor cycling is a popular and effective training format that can improve aerobic capacity, blood pressure, body composition, and lipid profiles [28, 29, 41, 115, 116]. Building on this potential, immersive training systems and cycling-based exergames have been developed to further increase engagement and motivation [11, 12, 20, 49, 67, 71, 80, 93, 96, 124], supported by evidence that game-based exercise interventions can improve engagement and persistence [60, 78]. A highly popular group exercise format is instructor-led indoor cycling, commonly referred to as “indoor cycling” or “Spinning®” [10], depending on the trainer’s license. Energizing music frequently accompanies these classes because it can reduce perceived exertion, enhance performance, and elicit positive emotional responses [105]. At the same time, indoor cycling is a high-intensity activity that benefits from close monitoring, particularly for beginners and less fit participants [26, 90].

Indoor cycling is also a particularly interesting setting for SportsHCI. Riders with different fitness levels train together in the same room, follow the same instructor, and remain part of the same shared activity rather than becoming physically separated. Group classes with instructors [84], dynamic music [105], and social interaction [39] can make training more engaging, yet technological support for richer gamification and explicit social interaction in co-located classes remains limited. Systems such as Polar Club [36] provide real-time heart-rate feedback for instructors and participants, but focus primarily on cardiovascular monitoring and offer only limited game-like or social mechanics during the class. Commercial platforms such as Peloton [89], NordicTrack [83], Wahoo [111], and Zwift [130] offer connected training ecosystems, but are typically oriented toward personal or proprietary setups rather than co-located group classes of 15 to 30 riders at scale. More broadly, there is still limited empirical understanding of how gamification and social interaction shape experience in indoor cycling classes.

This setting is especially promising because heart rate, cadence, and resistance are tightly coupled, while still allowing riders with very different fitness levels to train together. In a typical class, the instructor specifies target heart-rate zones and the music establishes a shared target cadence. Although individually optimal pedaling cadence can vary between cyclists [1], music-based indoor cycling

uses this shared tempo as a class-wide coordination cue. Participants then regulate their own resistance to reach these targets according to their individual fitness. As a result, heart rate and cadence can serve as shared feedback and interaction resources, while resistance remains the individualized control variable. This makes it possible to design cooperative or competitive interactions that do not depend on absolute fitness or power output alone, and instead allow beginners and experienced riders to participate meaningfully in the same activity.

To study this design space, we built on our previously developed open-source indoor cycling toolkit [62], which retrofits conventional mechanical indoor bikes with sensor technology for heart rate, cadence, and braking resistance and derives music synchronization in real time. On top of this setup, we implemented four conditions in a 2×2 design varying *Feedback Style* (*Dashboard* vs. *Game*) and *Social Setting* (*Single* vs. *Teams*). The *Dashboard* conditions were implemented as Flutter-based visualizations with lower gamification, whereas the *Game* conditions were realized as Unity-based visualizations with higher gamification. Likewise, *Single* emphasized individual performance with low social interaction, whereas *Teams* introduced team-based interaction with higher social dynamics. We evaluated these conditions in a within-subjects field study across four real Spinning® classes with $N = 61$ participants.

This paper reports a field study of music-synchronized group cycling that examines how feedback style and social setting shape user experience and synchronization in practice. Rather than identifying a single universally preferable design, the study highlights the value of designing for variety. Our work contributes empirical insights into heart-rate- and cadence-based sports data visualization for co-located group exercise, a context that remains underexplored in gamification research. More broadly, our findings inform the design of feedback systems for rhythm-oriented sports classes in which shared timing matters, such as rowing or Zumba®.

2 Related Work

Our work sits at the intersection of sensor-based indoor cycling systems, gamification and exergaming, social exercise, and music-synchronized movement. In the following, we first review prior work on instrumented cycling systems, then situate our feedback designs between gamification and exergames, and finally discuss social interaction and music synchronization as key design resources for indoor group cycling.

2.1 Sensor-Based Cycling Systems

Cycling has been augmented with a wide range of sensing technologies to capture performance and support interactive training. For example, the Exerlearn bike combined physical exercise with learning by integrating additional hardware such as handlebar buttons and hall sensors for cadence tracking [5]. Wu et al. presented SmarCyPad, a smart seat pad that uses conductive fabric sensors to estimate rider position, cadence, and knee joint angle, although it does not consider braking resistance [122]. Chander et al. showed that cadence can also be estimated with low-cost hardware by using smartphone acceleration data, achieving less than 2% deviation in RPM estimation [27]. Okugawa et al. proposed a pedaling training system based on a crank-mounted accelerometer and gyroscope,

but this setup requires wired sensing on a rotating component and is therefore mechanically more complex and less portable [86].

Beyond instrumentation, cycling HCI research has also explored interactive simulators, training systems, and exergaming setups [75, 76, 98]. Cycling exergames have been implemented on ergometers with (custom) sensors [5, 7, 8, 51, 63, 64, 97], direct-drive or on-wheel trainers [16], and smartphone-based solutions [27]. However, much of this work focuses on individual riders, virtual environments, or single-user interaction. In contrast, there is still limited support for scalable systems that simultaneously capture and visualize real-time data from many riders in co-located indoor cycling classes. This gap is particularly relevant for studying group dynamics, public feedback, and shared co-located training experiences.

2.2 Gamification and Exergames in Exercise and Cycling

Prior work has shown that gameful design can increase engagement and enjoyment in physical activity [44, 74]. At the same time, the boundary between *gamification* and *exergames* is not always sharp. Gamification is commonly defined as the use of game design elements in non-game contexts [32, 34, 35, 45, 52, 70, 102, 118, 119, 128], whereas exergames are typically understood as games in which physical exertion is a central part of the interaction or gameplay [2, 18, 19, 68, 81, 85, 106, 123]. Warsinsky et al. further distinguish gamification from serious games and exergames by arguing that gamification supplements an existing activity with gameful elements, while exergames make physical activity part of the game itself [117]. For our context, this distinction is useful but should not be overstated: the dashboard conditions in our study are clearly closer to gamification, whereas the game conditions move toward exergame-like feedback, even though both are built on the same instructor-led cycling activity.

Research on gamification in exercise suggests that its effects depend strongly on the concrete mechanics used. Reviews report generally positive effects on activity and enjoyment, but also note that many systems emphasize technical novelty more than motivational design [74]. Points, rankings, leaderboards, avatars, and progress visualizations are common elements [99]. Social comparison through leaderboards can motivate users, but may also create unwanted competitive pressure depending on context and user perception [58, 66]. Similarly, social gamification systems can promote healthier behavior when they balance individual goals and competition appropriately [127]. Prior work also highlights that users differ in how they respond to such mechanics, for example in relation to player types [14]. Moreover, gamified exercise systems should be designed carefully to avoid negative effects such as surveillance, overtraining, or overexertion [13, 65].

Exergame research further shows the potential of integrating physical performance directly into interactive systems [42, 125]. Cycling exergames have been widely studied [11, 12, 20, 46, 53, 67, 71, 80, 93, 104, 124, 126], often with custom sensing and adaptive mappings from pedaling to gameplay. For example, Hardy et al. proposed adapting game mechanics based on training parameters such as cadence [47], and Hein et al. used a virtual character to help cyclists stay in a target heart-rate zone during training [49]. Reviews also suggest that exergames can support short-term behavior

change and engagement, although long-term effects depend on sustaining appropriate intensity, duration, and motivation [107, 120]. Taken together, prior work suggests that indoor cycling is well suited for feedback systems that range from low-gamification dashboards to more game-like, immersive visualizations. However, most existing work has focused on individual exercise or virtual settings rather than instructor-led, co-located group classes.

2.3 Social Interaction in Exercise and Cycling

Social interaction is a central factor in physical activity and can increase enjoyment, motivation, and persistence [21, 43, 54, 79, 82, 113]. More generally, social reward and support can make exercise feel more energizing and enjoyable, and may even improve performance without increasing perceived effort [33]. Social interaction has also been described as a persuasive mechanism in fitness systems, for example through social competition, visibility, and contagion [22]. Likewise, perceived interdependence and support in group activities can contribute to well-being and motivation [30].

For cycling specifically, prior work suggests that shared physiological data can enrich co-located exercise. Walmlink et al. explored a helmet-mounted heart-rate display and showed that making heart-rate data visible to others can foster social interplay and engagement during exertion [112]. Agharazidermani et al. developed a collaborative heart-rate display for cycling partners and found that shared real-time heart-rate feedback may facilitate dialogue and support collaboration, especially for less experienced riders [3]. These studies show the design potential of publicly or collaboratively visible exercise data, but focus on pairs rather than full classes.

Related work on group exercise further underscores the importance of co-located social settings. Beck et al. found that indoor cycling in a group session was experienced as more enjoyable than training individually, even without performance differences [15]. In gamified or exergame contexts, social elements have also been used to support cooperation and motivation, for example in tandem-based VR cycling experiences [53]. Overall, prior work suggests that social exercise systems can benefit from both competitive and cooperative mechanisms, yet the effects of such mechanics in larger, instructor-led indoor cycling classes remain underexplored.

2.4 Music and Synchronization in Group Exercise

Music is a core component of many indoor cycling classes and can shape both motivation and movement. In cycling contexts, music has been shown to improve emotional response, reduce fatigue, and enhance enjoyment [103, 105]. More broadly, synchronizing movement to music can also support performance: Karageorghis et al. found that running in synchrony with music improved sprint performance compared to neutral music or no music [59]. These findings suggest that music is not merely background stimulation, but can act as a temporal structure for physical activity.

Synchronization is also socially meaningful. Cohen et al. showed in rowing that synchronized group movement was associated with elevated pain thresholds and stronger euphoric effects [31]. In cycling, Wang et al. found that two-person synchronized cycling

improved subsequent cooperation and accelerated cooperative decision making [114]. These results indicate that synchronization can strengthen not only individual experience but also social cohesion.

Prior work has further begun to connect synchronization with playful and interactive exercise systems. Park et al. proposed Exer-Sync, a social exergame that used rhythmic cues to encourage synchronized movement, including prototypes for indoor cycling [88]. Their results suggest that playful synchronization cues can enhance user experience and enjoyment, even when objective synchronization does not necessarily improve. In VR exergaming, synchronization with music rhythm has also been explored to increase enjoyment and motivation during high-intensity exercise [17, 61, 126], although effects may depend on whether users can consciously perceive the synchronization and whether the added coordination effort is worthwhile [6]. For indoor cycling, this is especially relevant because instructors already use music to communicate target cadence. This makes music-synchronized feedback a particularly promising design resource for co-located group classes.

In summary, prior work motivates our focus on music-synchronized, sensor-based group cycling, but it also reveals an open gap. Existing research has studied instrumented bikes, gamified and exergame-based exercise, social exercise systems, and rhythmic synchronization, yet these strands have rarely been combined in real, instructor-led indoor cycling classes. Our work addresses this gap by investigating how feedback style (*Dashboard* vs. *Game*) and social setting (*Single* vs. *Teams*) shape user experience and synchronization in co-located Spinning® classes.

3 Study Concept and Design Rationale

This work investigates how the representation of feedback and the degree of explicit social interaction shape the experience of music-synchronized indoor cycling. Rather than changing the underlying exercise task, we vary how performance is made visible and how participants are socially coupled during the class. Across all conditions, participants aim to match a target heart-rate zone and a target cadence derived from the music, while adjusting resistance individually to their own fitness level. Our research question is: *How do feedback style and social setting shape user experience and synchronization in co-located, music-synchronized indoor cycling classes?*

To study this question, we realized a 2×2 design with the factors *Feedback Style* (*Dashboard* vs. *Game*) and *Social Setting* (*Single* vs. *Teams*), resulting in four conditions: *Dashboard Single* (DS), *Dashboard Teams* (DT), *Game Single* (GS), and *Game Teams* (GT). We use *Feedback Style* as an operationalization of lower versus higher gamification. The *Dashboard* conditions present sensor-derived performance information directly and numerically, whereas the *Game* conditions translate the same underlying performance logic into a more playful and abstract visual representation. In this sense, the *Game* conditions move closer to exergame-like feedback, while the *Dashboard* conditions remain closer to gamification. We use *Social Setting* as an operationalization of lower versus higher social interaction. Importantly, none of the conditions are fully non-social, because all participants train together in the same room and can see shared public feedback. The *Single* conditions foreground individual performance and live comparison without explicit collaboration.

The *Teams* conditions add explicit team structure and shared consequences, combining cooperative coordination within the team with competitive dynamics between teams. This framing allows us to compare four variants that share the same sensing infrastructure, training plan, and target-adherence logic, while systematically varying only the representation of feedback and the degree of explicit social interaction.

4 System Implementation and Condition Realization

We implemented an end-to-end system that retrofits conventional mechanical indoor cycling bikes with real-time sensing and connects these data to private and public feedback displays. To present the system as an integrated pipeline, this section follows the flow from sensing to visualization: we first describe the sensor-based bike setup, then the real-time data processing and Personal Control Panel, followed by the shared target-adherence scoring model, the Public Performance Feedback, and finally the realization of the four study conditions. Across all conditions, the same sensing infrastructure and training logic were used: participants aimed to match a target heart-rate zone and a target cadence derived from the music, while the system continuously evaluated target adherence and forwarded the resulting state to the visualizations.

4.1 Sensor-Based Bike Setup

Our retrofit kit, described in further detail in prior work [62], provides the sensing infrastructure for this field study by attaching to indoor cycling bikes with mechanical flywheels and measuring heart rate, cadence, and braking resistance (Figure 2). Each bike uses an ESP32 NodeMCU [56] running firmware developed with PlatformIO [92] and the Arduino framework [9]. Heart rate is captured with Polar OH1 sensors [38, 50] via Bluetooth Low Energy. Cadence is detected using two reed switches mounted near the pedals and triggered by magnets attached to the pedals, which also allows us to distinguish left and right pedal strokes. Braking resistance is inferred from an analog thin-film pressure sensor [57] mounted between the brake adjustment screw and the brake block. To support deployment on a full class of bikes, we designed 3D-printed mounts for the housing, adjustable reed-switch positioning, and pressure-sensor fixation. Additional construction details of the retrofit kit are shown in the Appendix A (Figure 7).

To relate pedaling to the music, we treat one full pedal revolution as corresponding to two beats. Accordingly, a cadence of 70 revolutions per minute (RPM) matches a song tempo of 140 beats per minute (BPM). Because this mapping is more intuitive in a music-based indoor cycling class, the visualizations display cadence as doubled RPM values that can be compared directly to the musical beat. This also supports half-time and double-time interpretations when needed in slower/faster songs and training sections like sprints [1].

4.2 Real-Time Data Processing and Personal Control Panel

All sensor data is transmitted via Wi-Fi to a central server, where it is stored, aligned with the music timeline, and distributed to the connected clients in real time. The server maintains the current

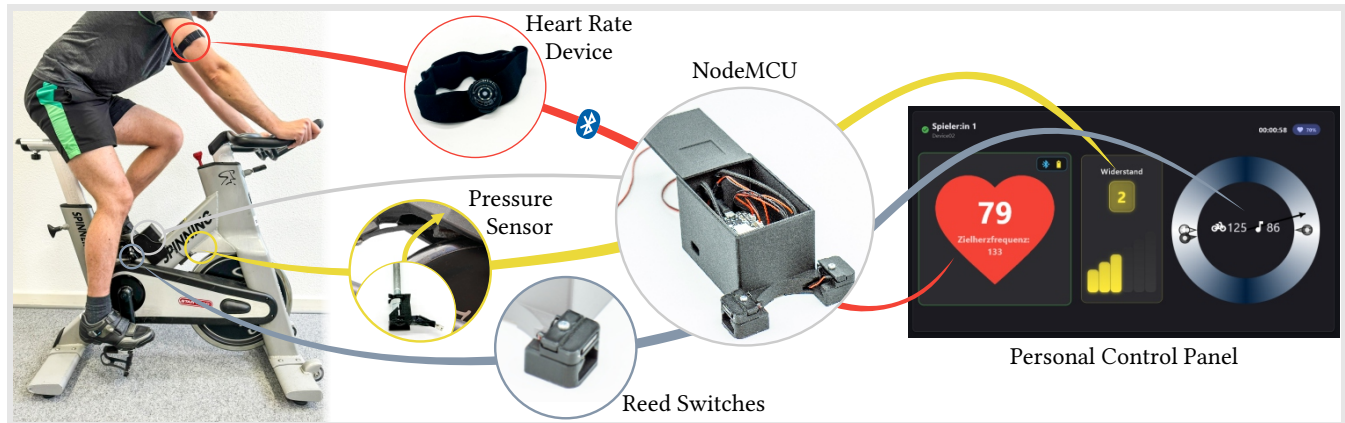


Figure 2: System overview. Left: placement of the retrofit hardware and sensors on the bike and rider. Middle: the sensor kit receives heart rate via Bluetooth and cadence and braking-resistance data via wired sensors. Right: the Personal Control Panel shown on the participant tablet during training, displaying heart rate, resistance, cadence, and beat-synchronization feedback.

training state, including the active target heart-rate zone, current music BPM, and derived beat timings.

On each bike, an Android tablet shows a private *Personal Control Panel* that supports self-regulation during training. This view displays the current heart rate and target heart rate, the current braking-resistance level as a coarse class, the current cadence and music BPM, and a circular metronome-like visualization that compares left and right pedal strokes with the beat. The header additionally shows participant identification, connection status, elapsed time, and the currently active target heart rate as a percentage value. This participant-facing view was identical across all four conditions and ensured that every rider had access to the same core performance information in every condition, independent of the public visualization.

4.3 Target-Adherence Scoring

To implement comparable conditions across *Dashboard* and *Game*, we used a shared server-side scoring model based on heart-rate and cadence adherence. Once per second, the server compares target and actual values and awards points separately for heart rate and cadence. A (near-)perfect match receives 100 points if the heart rate is within $\pm 2\%$ of the target or cadence is within ± 5 BPM, respectively. A weak match receives 25 points if heart rate is only within $\pm 10\%$ of the target or cadence only within ± 20 BPM. Values between these thresholds are interpolated linearly. The minimum score for weak matches was intended to acknowledge partial effort and reduce frustration when participants did not reach the target range. No points are awarded when no cadence is detected, preventing rewards while not pedaling.

The server additionally generates event flags such as "perfect heart rate" and "perfect cadence", which trigger visual feedback in both dashboard and game clients. In the *Teams* conditions, individual scores are aggregated at team level and normalized for unequal team sizes by scaling the smaller team to the size of the larger one. We further implemented two team actions to increase explicit social interaction: a cadence bonus, triggered when at least 70% of a team rides within ± 5 BPM of the target, and a heart-rate event, triggered when at least 70% of a team simultaneously reaches the narrow heart-rate target threshold of $\pm 2\%$. The cadence event

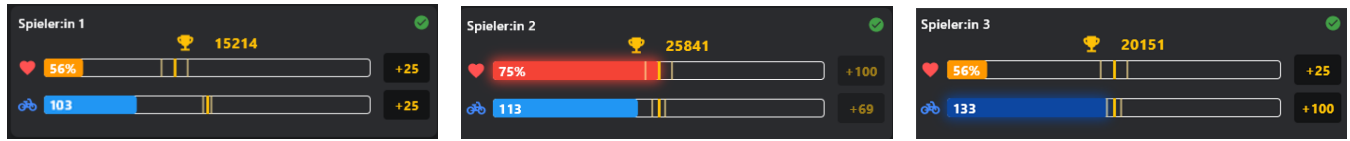
adds bonus points to the triggering team, whereas the heart-rate event subtracts points from the opposing team with a one-minute cooldown.

4.4 Public Performance Feedback

The projected *Public Performance Feedback* formed the experimental manipulation. We realized the four study conditions by combining two feedback styles and two social settings while keeping the sensing and scoring logic constant.

Dashboard feedback. The *Dashboard* conditions used a shared grid of participant tiles, shown in Figure 3. Each tile displayed the participant's name, connection status, two metric bars for heart rate and cadence, current values, target markers and zones, and per-step reward feedback. When a target zone was met, the corresponding bar was highlighted with a color and glow effect. In *Dashboard Single*, tiles additionally displayed accumulated individual scores. In *Dashboard Teams*, tiles retained per-step feedback on the right side but removed individual totals at the top in favor of team-level summaries.

Game feedback. The *Game* conditions translated the same target-adherence logic into a more playful city-building visualization. We chose this theme as an authorial design choice to deliberately move away from common cycling or racing metaphors and from direct representations of speed, power, or heart-rate competition. The city-building metaphor allowed participants' performance to accumulate toward a visible outcome without foregrounding numerical metrics, thereby creating a clearer contrast to the Dashboard conditions. Participants were represented as customizable, walking avatars with floating heart-rate and cadence bars and displayed names. Reaching the targets changed the avatar outline color as a glowing aura (red for heart rate, blue for cadence, magenta for both). Instead of showing scores numerically, points were mapped to house construction progress: new points gradually built houses from construction sites to completed buildings. These shared visual building blocks were identical in *Game Single* and *Game Teams*; Figure 4 illustrates them as the core visual feedback elements of the *Game* conditions, comprising avatar-based target feedback and house-based progress visualization.



(a) Neither target reached

(b) Heart rate target reached

(c) Cadence target reached

Figure 3: Participant tiles used in the *Dashboard* conditions. The tile shows heart rate and cadence bars with target markers and zones, and highlights the corresponding metric with a glow effect when the rider is within target range.



(a) Heart rate target reached

(b) Cadence target reached

(c) Both targets reached



(d) Newly spawned building

(e) Partially constructed building

(f) Fully constructed building

Figure 4: Core visual feedback elements used in the *Game* conditions. Top row: avatar-based feedback, indicated by outline color (aura) and progress bars for heart rate and cadence. Bottom row: house construction as a game-based representation of progress over time.

Figure 5 summarizes the projected *Public Performance Feedback* in the four study conditions. While all conditions are based on the same sensing and target-adherence logic, they differ in how performance is represented and how social interaction is structured. The *Dashboard* conditions visualize target adherence directly through participant tiles and score displays, whereas the *Game* conditions translate the same logic into avatar- and city-building-based feedback. The *Teams* conditions additionally introduce explicit team structure (left vs. right) and shared consequences.

4.5 Realization of the Four Study Conditions

Building on the shared sensing, scoring, and feedback infrastructure described above, the four conditions instantiated the two experimental factors by varying how performance was represented and how social interaction was structured.

Dashboard Single (DS) (Figure 5a) implemented lower gamification and lower explicit social interaction. The shared screen showed

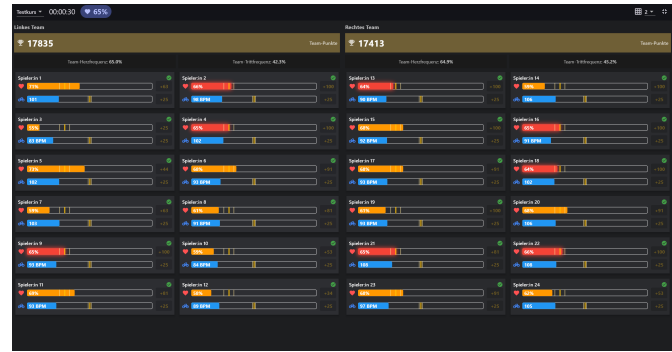
a grid of participant tiles, one per rider, with individual accumulated scores and current target adherence. Participants could compare themselves to others, but no explicit collaborative mechanics were introduced.

Dashboard Teams (DT) (Figure 5b) retained the same tile-based representation but split the class into a left and a right team according to their physical position in the room. The top area of the screen displayed team scores and aggregated team metrics. Team synchronization events for heart rate and cadence were visualized as shared dashboard events using background coloring and a lightning animation.

Game Single (GS) (Figure 5c) implemented higher gamification with lower explicit social interaction. Using the avatar- and house-based feedback vocabulary shown in Figure 4, each participant was assigned a separate tile showing a small city area in which their avatar moved and built houses according to individual performance.



(a) Dashboard Single (DS)



(b) Dashboard Teams (DT)



(c) Game Single (GS)



(d) Game Teams (GT)

Figure 5: Public Performance Feedback in the four study conditions. The *Dashboard* conditions visualize target adherence directly through participant tiles and score displays, whereas the *Game* conditions translate the same logic into city-building progress and avatar-based feedback. The *Teams* conditions add explicit team structure and shared consequences.

This preserved the single-player logic while replacing numerical progress with a game-like visualization.

Game Teams (GT) (Figure 5d) combined the game representation with explicit team interaction. Using the same avatar- and house-based feedback elements shown in Figure 4, all participants were placed on a shared map divided into two sides by a river and connected by a bridge, with one side per team. Each team jointly built a city, so individual performance contributed to shared construction progress. Team actions were visualized as game events: cadence synchronization bonuses accelerated building progress, whereas heart-rate synchronization events spawned an excavator that crossed the bridge and destroyed an opposing building.

All four conditions ended with a short result phase. In the *Single* variants, the system highlighted the best individual performances for heart-rate adherence, cadence adherence, and estimated power output (based on cadence and braking resistance over time). In the *Teams* variants, the result phase compared both teams on the same categories using only team-aggregated values. While the *Dashboard* conditions presented these outcomes as numerical comparisons, the *Game* conditions translated them into a short award ceremony with a winner podium for the best three riders or the winning team. Detailed individual results remained visible only on the Personal Control Panel, while the *Public Performance Feedback* was limited

to the top three riders in the *Single* variants or the winning team in the *Teams* variants, thereby avoiding public exposure of lower-performing riders.

5 Field Study

We evaluated the four study conditions in four real university Spinning® classes. The field study examined how *Feedback Style* (*Dashboard* vs. *Game*) and *Social Setting* (*Single* vs. *Teams*) shape user experience, workload, flow, synchronization, and preference in practice. Because participants were already familiar with the gym's standard Polar Club (PC) setup [36], we additionally included PC as a familiar baseline in the final preference ranking, but not as part of the 2×2 repeated-measures design, since it provides only heart-rate visualization and no cadence-based feedback.

5.1 Study Design and Apparatus

We conducted a within-subjects field study in four one-hour Spinning® classes at a university sports club. Each class included all four study conditions (DS, DT, GS, and GT) within the same session. The condition order was not fixed across classes, but counterbalanced using a balanced Latin square [95] to reduce order effects such as learning, fatigue, or adaptation. Because participants attended their

regular classes and class sizes varied naturally, perfect counterbalancing across all participants was not possible. We therefore used a balanced subset for the main repeated-measures analysis.

The study took place in a cycling room with 24 participant bikes arranged in four rows of six, plus one additional bike for the instructor at the front of the room. Each participant bike was equipped with our retrofit sensor kit, a Polar OH1 heart-rate sensor, and an Android tablet mounted on the bike. During the condition blocks, riders therefore had two information sources: a private Personal Control Panel on their bike-mounted tablet, showing individual real-time feedback, and the projected Public Performance Feedback on the wall next to the instructor, showing the condition-specific class-wide visualization. The room layout allowed a left-versus-right split for the *Teams* conditions, while all riders remained surrounded by other participants in the shared class setting.

Before the main study, we conducted repeated technical test runs and a pilot deployment with 14 non-study participants from our lab to validate timing, sensing, visualization visibility, and the overall procedure. This helped stabilize the study flow and improve the reliability of the deployment for full-class use.

5.2 Procedure and Measures

Before the session, participants provided informed consent and entered demographic and study-related information on their bike-mounted tablets, including display name, age, maximum heart rate, preferred leading foot for beat alignment, and avatar selection for the *Game* conditions. If participants did not know their maximum heart rate, the system estimated it using the common approximation $HR_{\max} = 220 - \text{age}$, consistent with the regular Polar Club-based classes [37]. We used this approximation to preserve ecological validity and continuity with participants' usual training routine, while acknowledging that more recent formulas, such as $HR_{\max} = 208 - 0.7 \times \text{age}$, may provide more accurate estimates [109].

Each class began with a two-minute warm-up at 65% of the configured maximum heart rate to familiarize participants with the personal and public feedback displays. No points were awarded during this warm-up. The study then proceeded through four condition blocks of eight minutes each. Before every block, we explained the upcoming visualization and mechanics. All four conditions used the same predefined training plan and edited music playlist, with timestamp-based target heart-rate values and cadence targets. The detailed training plan is provided in the Appendix A (Figure 8). During all condition blocks, the system continuously recorded heart rate, cadence, and braking resistance. From these signals, we derived objective performance and synchronization measures, including adherence to target heart rate and cadence, cadence deviation from the target, and cadence deviation from the group mean.

After each condition, participants continued pedaling at low intensity while first viewing the result phase and then completing the questionnaires directly on their tablets. This phase also served as a short active recovery period. We combined standardized measures with study-specific items: UEQ-S [101], the Flow Short Scale [94], and NASA-TLX [100], as well as custom 7-point Likert items on perceived heart-rate synchronization and perceived beat synchronization, and two enjoyment items ("I had fun playing this game." and "In this session, I enjoyed moving.").

After the final condition, participants ranked all four study conditions alongside the familiar Polar Club system from their usual Spinning® sessions. The session then ended with a cool-down and stretching phase to reduce the risk of injury. Afterwards, we conducted semi-structured group interviews with participants and individual interviews with the two course instructors to capture perceptions that were not accessible through the quantitative data alone. Participant interviews were conducted in groups to accommodate the large number of riders per class while still allowing everyone who wished to contribute to share their impressions. The interviews were conducted immediately after the class session, followed a prepared semi-structured interview guide, and focused on participants' and instructors' experiences with the four conditions, perceived differences between them, and suggestions for future use.

5.3 Ethics and Bias Mitigation

The study was conducted in accordance with institutional ethical guidelines and received approval from our ethics committee. Before participation, all participants received a written explanation of the procedure and provided informed consent. Because the study involved physically demanding exercise, participants were informed that they could stop at any time in case of discomfort. To reduce injury risk, the session included a guided warm-up before the study blocks and a cool-down with stretching afterwards. No photos or videos were taken during the study, as we wanted to avoid additional pressure in a setting where participants were exercising in close-fitting sportswear and under substantial physical exertion. Interview recordings were transcribed, pseudonymized, and deleted after completion of the project.

Because the study was conducted in regular classes at a university sports club, we also considered potential researcher-participant familiarity. The first author regularly attended classes at the study site and knew the instructors and some participants, but did not conduct the participant group interviews. These interviews were conducted by other authors or research associates who did not participate in the classes and were not familiar with the participants. This was intended to reduce social-desirability effects in participant responses. The instructor interviews were conducted separately. Nevertheless, the co-located class setting and group-interview format may still have influenced participant behavior and responses through mutual presence, discussion, or perceived expectations.

5.4 Participants

A total of $N = 61$ participants took part in the field study across four Spinning® classes held over one week, including two beginner and two advanced classes. Participants were between 22 and 78 years old ($M = 36.97$, $SD = 14.02$); 31 identified as women and 30 as men. We also collected self-reported indoor-cycling experience and attendance frequency. The full sample was overall experienced: 7 participants reported 0–3 months of prior Spinning® experience, 5 reported > 3 and < 6 months, 6 reported > 6 and < 12 months, 11 reported > 1 and < 2 years, and 32 reported more than 2 years. Attendance frequency was similarly high: 12 participants attended 1–3 classes per month, 36 attended about one class per week, 10 attended about two classes per week, and 3 attended three or more

classes per week. Overall, the sample therefore consisted predominantly of regular and experienced riders.

For the main repeated-measures ANOVA, we selected a balanced subset of $n = 44$ participants to ensure equal observations across the four counterbalanced condition orders. This analysis sample was between 22 and 78 years old ($M = 37.84$, $SD = 14.33$) and included 24 women and 20 men. Its experience profile remained similar to the full sample: 4 participants reported 0–3 months of prior Spinning® experience, 4 reported > 3 and < 6 months, 4 reported > 6 and < 12 months, 7 reported > 1 and < 2 years, and 25 reported more than 2 years. Attendance frequency was distributed as follows: 10 participants attended 1–3 classes per month, 24 attended about one class per week, 8 attended about two classes per week, and 2 attended three or more classes per week. Thus, the analysis sample was likewise dominated by more experienced riders, which also motivated additional subgroup analyses.

5.5 Results

Quantitative analyses focused on a balanced subset of $n = 44$ participants and used repeated-measures 2×2 ANOVAs with *Feedback Style* (Dashboard vs. Game) and *Social Setting* (Single vs. Teams) as within-subjects factors. We then complement these findings with the final ranking data and the post-study interviews.

5.5.1 Quantitative Results. The Appendix A provides supplementary tables for readers who want to inspect the statistical results in tabular form. Table 1 summarizes the repeated-measures ANOVA results for the main analysis, and Table 2 reports the corresponding pairwise contrasts; measures for which no significant effects emerged (e.g., heart-rate target adherence and various subscores of the standardized questionnaires) are omitted.

Across the quantitative measures, the clearest differences emerged between *Dashboard* and *Game*. *Dashboard* was perceived as more pragmatic than *Game* ($F(1, 120) = 12.2971$, $p = .0006$, $\eta_p^2 = .0930$; Dashboard: Med. = .25, IQR = 1.75, Game: Med. = -.25, IQR = 1.75) and supported higher flow fluency ($F(1, 120) = 6.7887$, $p = .0103$, $\eta_p^2 = .0535$; Dashboard: Med. = 4.40, IQR = 1.95, Game: Med. = 4.10, IQR = 1.40). In contrast, *Game* was rated as more hedonic ($F(1, 120) = 9.2719$, $p = .0029$, $\eta_p^2 = .0717$; Game: Med. = 1.25, IQR = 1.62, Dashboard: Med. = .75, IQR = 1.88) but also as more mentally demanding ($F(1, 120) = 9.9458$, $p = .0020$, $\eta_p^2 = .0765$; Game: Med. = 62.50, IQR = 32.50, Dashboard: Med. = 45.00, IQR = 33.75).

For *Perceived Beat Synchrony*, we found significant main effects of both *Feedback Style* and *Social Setting*. Participants reported higher synchrony in *Dashboard* than in *Game* ($F(1, 120) = 4.6492$, $p = .0331$, $\eta_p^2 = .0373$; Dashboard: Med. = 5.00, IQR = 2.00, Game: Med. = 4.00, IQR = 2.00) and in *Teams* than in *Single* ($F(1, 120) = 6.7610$, $p = .0105$, $\eta_p^2 = .0533$; Teams: Med. = 5.00, IQR = 2.00, Single: Med. = 4.00, IQR = 2.00). No interaction between the two factors emerged.

This pattern was partly reflected in the objective cadence data. For *Mean BPM Deviation from Group Mean*, *Dashboard* yielded lower deviation than *Game* ($F(1, 120) = 13.3251$, $p = .0004$, $\eta_p^2 = .0999$; Dashboard: Med. = 20.78, IQR = 6.22, Game: Med. = 23.42, IQR = 6.16), indicating closer synchronization with the class rhythm. In the full sample, no significant main effect of *Social Setting* emerged for this measure, although the descriptive statistics pointed in the same direction as the subjective synchrony ratings (Teams: Med. = 21.12,

IQR = 6.07, Single: Med. = 23.04, IQR = 5.63). Measures related to heart-rate target adherence did not show condition-specific differences and are therefore not discussed further.

We additionally inspected two subgroups to better understand potential moderators. The subgroup ANOVA tables and corresponding pairwise contrasts are reported in the Appendix A: for the younger subgroup (< 40 years) in Tables 3 and 4, and for the Spinning®-experienced subgroup in Tables 5 and 6. As above, measures for which no significant effects emerged are omitted. In a younger subgroup (< 40 years), the same *Dashboard* versus *Game* pattern became more pronounced across user experience, mental demand, flow, and synchronization measures, and objective synchrony (Mean BPM Deviation from Group Mean) additionally favored *Teams* over *Single*. In a highly experienced subgroup (> 2 years of prior Spinning® experience), the overall direction of effects remained similar, while the clearest additional result was higher *Perceived Beat Synchrony* in the *Teams* conditions.

5.5.2 Condition Ranking. To summarize participants' final preferences, we analyzed the ranking data using two complementary measures: *first-place share*, that is, the percentage of times a condition was ranked first, and Borda scores [91], which assign 1–5 points based on placement and therefore provide a more comprehensive view of the ranking than first-place selections alone. Figure 6 shows these results, with Figure 6a summarizing the overall ranking and Figure 6b visualizing first-place choices across age groups.

Dashboard Single achieved the highest Borda score, whereas *Game Single* was most frequently ranked first. Overall, the familiar Polar Club system ranked below the four study conditions in terms of Borda score, although it still received a noticeable share of first-place rankings. Across conditions, the *Single* variants tended to rank higher than the *Teams* variants. The age-stratified heat map further suggests that first-place preferences were distributed across age groups and that the familiar Polar Club system was not primarily preferred by older participants, contrary to our initial expectation. However, these age patterns should be interpreted cautiously, as some of the older age bins contain only very small numbers of participants.

5.5.3 Qualitative Results. After the final condition, we conducted semi-structured group interviews with 55 of the participants in 23 interview sessions of one to seven people, as well as individual interviews with the two course instructors. All interviews were transcribed and analyzed using thematic analysis [4, 23, 24]. Two authors conducted open coding and then discussed and refined the codes with two additional authors to form themes capturing key findings. Because participant interviews were conducted in groups of varying size, we report qualitative prevalence at the session level: a theme was counted once per interview session when it occurred at least once, regardless of how many individuals mentioned it. Participant quotes are labeled with a pseudonymized identifier $I\#\#P\#$, where $I\#\#$ denotes the interview session and $P\#$ the participant index within that session; instructor/trainer quotes are labeled $T1$ and $T2$. The interview excerpts below were translated by the authors with an emphasis on preserving meaning. In the following, we report our final themes:

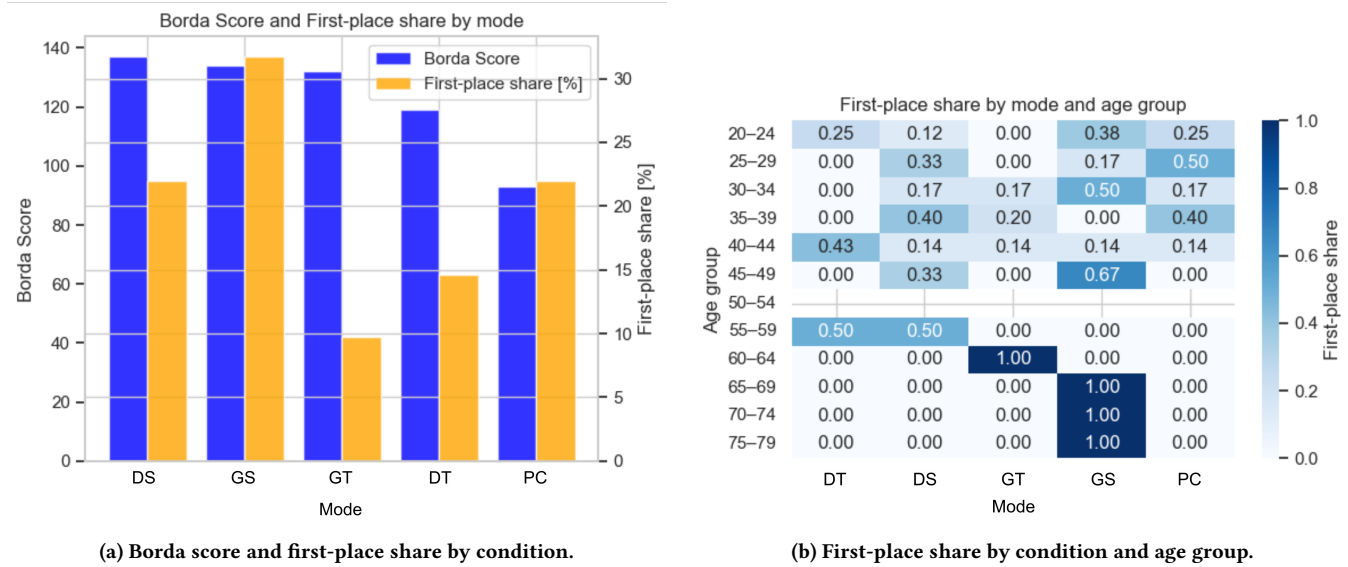


Figure 6: Final ranking of the four study conditions (DS: Dashboard Single; DT: Dashboard Teams; GS: Game Single; GT: Game Teams) and the familiar Polar Club (PC) system. (a) Overall ranking results shown as Borda score and first-place share. (b) Heat map of first-place choices across age groups.

General reception and novelty. Overall reception was broadly positive, although positive reception was not explicitly discussed in every interview session. Across 12 of 23 interview sessions, participants described the study as a positive experience; in 10 sessions, they explicitly stated that the training was fun, and in 8 sessions they described it as more exciting than their usual class. The remaining sessions should not be interpreted as negative by default, but rather as sessions in which participants focused on more specific aspects of the experience, such as training intensity, synchronization, readability, or preferences between conditions. Positive reactions were often expressed very directly, such as: “It was cool, it was fun” (I06P1). At the same time, several participants emphasized that the augmented setup should complement rather than replace the established class routine. As one participant put it, “It was interesting, but I think the normal training is better” (I03P1).

Training intensity and regulation. Participants frequently reflected on the effort required to regulate their training to the targets. In 11 sessions, the training was described as less strenuous than usual, whereas in 9 sessions participants reported similar exertion across conditions. Some also described the task as mentally demanding, for example: “I found it a bit stressful” (I14P1). Cadence regulation emerged as the more difficult component. In 6 sessions, participants described the target cadence as hard to reach, for instance: “I had the feeling that sometimes you had to pedal really fast” (I12P1). In 3 interview sessions, participants stated that the heart-rate target was easier to reach than the cadence target, likely because they were already familiar with this metric from regular Polar Club use.

Music and beat synchronization. Synchronizing pedaling with the music was a central topic throughout the interviews. In 8 sessions, participants described riding in sync as difficult, for example: “I also had real problems keeping in sync with the music” (I11P2). In

contrast, other participants described synchronization as manageable or well supported by the system: “Keeping in time was fairly easy” (I17P2). The metronome-like visualization on the Personal Control Panel was repeatedly highlighted as useful; one participant stated: “The metronome is what I liked best [...] I thought that was really good. The way it spun around really helped me” (I20P1). At the same time, in 4 sessions the metronome was described as initially confusing, suggesting that beat support itself required a short adaptation phase. Participants also linked successful synchronization to music selection: songs with a clearer beat were described as easier to follow, and music more generally was mentioned as motivational in 4 sessions. Overall, cadence feedback was repeatedly valued as a useful addition to the familiar heart-rate-centered Polar Club setup, and in 9 sessions participants explicitly described the cadence display as a helpful extension for training.

Clarity and cognitive load. Participants frequently contrasted the two feedback styles in terms of readability and interpretability during exertion. Across 10 sessions, they reported initial difficulties, while 12 sessions referred to a learning effect over time; as one participant summarized, “It got better the more sessions we did” (I06P1). Dashboards were clearly perceived as more transparent than games: in 10 sessions, participants stated that dashboards were easier to understand, for example: “I found it easier to see on the dashboard” (I22P1). By contrast, game visualizations were more often described as harder to parse under workout conditions: “In the game mode, I found the interface a bit unclear, so it was difficult to see everything properly” (I10P2). This was not only attributed to the visualization logic itself, but sometimes also to the physical class environment. In 6 sessions, participants stated that avatars were difficult to distinguish when too close together, and additional visibility issues arose because some participants did not

wear glasses while exercising or because other riders partly blocked the projection. Together, these accounts suggest that cognitive load and clarity were shaped by both interface design and the realities of the co-located classroom setup.

Gamification and social interaction as mixed motivational resources. Participants expressed heterogeneous preferences regarding both gamification and social interaction. Some welcomed the playful framing, as illustrated by comments such as “It is a matter of personal preference. I am more of a gamer” (I09P1) and “I found it fun that it was gamified like that” (I19P1). Others explicitly rejected gamification in this context: “I am not a gamer, I have never done that” (I03P1). This mixed picture also appeared in social mechanics. In 10 sessions, participants stated that team spirit increased motivation; one participant explained: “When we worked as a team, I felt a stronger obligation to put in genuine effort and do it correctly, because I felt responsible not only for myself but for the entire team” (I04P2). Instructor T2 similarly described the team setup as useful because “having a right team and a left team lets you nudge people a bit to focus on it.” At the same time, team dynamics could also create pressure. In 3 sessions, participants explicitly described team modes as stressful, for example: “The team events put me under pressure, because I felt I had to perform well; failing felt much more uncomfortable in the group than alone” (I05P3). In addition, 6 sessions mentioned that team scoring can mask weaker individual performance, whereas in 8 sessions participants described the *Single* variants as especially motivating because they allowed more direct self-comparison and self-pacing: “I think the single mode was more motivating because you could push yourself harder and try to perform better” (I11P2). From the instructor perspective, social interaction remained a core part of the class format; as T1 put it, “If there were no interaction, an AI could do it just as well.”

Adoption and deployment. When discussing future use, participants most often named *Dashboard Single* as the most desirable option for regular training, while others preferred a flexible combination of *Single* and *Teams* modes. Some participants explicitly expressed willingness to use the system again, for example: “I think I’d like to continue using it in general” (I06P1), while also emphasizing the value of optionality: “I would like to have both [single and teams]” (I08P2). Beyond the existing modes, participants suggested extensions such as game visualizations directly on the personal tablet or the use of the system as a kind of personal coach for home workouts. Across these accounts, adoption appears to depend on clarity, optionality, and low-friction integration into the established class routine. Both instructors emphasized gradual deployment: T1 suggested starting beginners with direct values in the *Dashboard* conditions and “add[ing] the games a bit later to add more variety,” while T2 similarly argued that dashboards are better for beginners because “they can see what they are doing,” whereas game and team variations may become more appealing for advanced riders once they are familiar with the system. More broadly, both participant and instructor feedback suggested that variety itself is valuable for sustaining engagement over time; as T1 noted, “I would probably vary it from week to week.”

6 Discussion

This work investigated how *Feedback Style* (*Dashboard* vs. *Game*) and *Social Setting* (*Single* vs. *Teams*) shape user experience and synchronization in co-located, music-synchronized Spinning® classes. The clearest and most robust effects were driven by *Feedback Style*, whereas *Social Setting* produced more selective effects centered on synchronization and group dynamics.

6.1 Dashboard vs. Game: Direct Feedback Supports Training, Game Feedback Adds Experiential Value

The strongest pattern across the quantitative and qualitative results is the split between a more pragmatic *Dashboard* and a more hedonic *Game*. *Dashboard* was perceived as more pragmatic, less mentally demanding, and more fluent, while *Game* was rated as more hedonic. Participants likewise described the dashboards as easier to understand during exertion, whereas the game conditions required a learning phase and more interpretive effort. This suggests that in an intensive exercise setting, the representation of feedback matters at least as much as the presence of game elements themselves. This also helps explain why *Dashboard* supported higher flow fluency, as direct feedback likely let riders spend less effort interpreting the display and more effort maintaining rhythm and target adherence [73, 74, 129]. This connects our field data to prior work suggesting that feedback, challenge, and reward structures are central to exergame enjoyment, but that their effects depend on how easily users can interpret and act on them during exertion [73, 74]. In our case, the gameful layer added hedonic value, but the direct dashboard better supported the concentration, feedback, and low cognitive overhead needed for flow during intensive training [108].

This pattern is plausible because the dashboard presents performance values directly and numerically, allowing riders to see their current state without first translating the visualization. By contrast, the game used the same sensing and scoring logic, but mapped it to avatars, houses, and events, trading immediate readability for a more experiential representation. This differs from many cycling exergames and virtual cycling systems that map performance to racing, navigation, or virtual opponents [16, 49, 67, 80]. Our field study adds a co-located class perspective: in this setting, the central design challenge is not only to make exercise more playful, but also to keep public feedback rapidly interpretable from a shared room display during physical exertion. At the same time, the *Game* conditions were not simply inferior: their higher hedonic quality, the relatively strong ranking of *Game Single*, and interview statements that the workout felt more entertaining or passed faster suggest that game-like feedback can provide meaningful experiential value. Our findings therefore do not argue against gamification in indoor cycling; instead, they indicate that gameful feedback works best as an optional layer on top of lightweight performance feedback.

6.2 Social Setting Primarily Affected Synchronization

Compared with *Feedback Style*, the effects of *Social Setting* were more specific. The clearest social effect was that participants reported better beat synchronization in the *Teams* conditions than

in the *Single* conditions. This tendency was partly reflected in the objective cadence data and became more pronounced in some subgroups. Thus, team structure did not broadly improve user experience, but it did seem to strengthen the experience of shared timing. This qualifies prior findings that group-based indoor cycling can be more enjoyable than individual exercise [15]: in our sensor-mediated setting, adding explicit team mechanics did not uniformly improve user experience, but primarily redirected attention toward shared rhythm, synchronization, and accountability.

The interviews suggest several reasons for this. Participants described team conditions as increasing awareness of a shared tempo through team spirit, accountability, competition, and direct comparison, while the instructors similarly described the left-versus-right setup as a way of focusing riders on the collective rhythm. This is consistent with prior work showing that synchronization in exercise is socially meaningful and that rhythmic social cues can enhance perceived alignment even when objective synchronization changes less strongly [31, 88, 114]. It also resonates with recent work on co-located cooperative exergames, which highlights that social exercise dynamics are shaped not only by competition, but also by cooperation, visibility, and shared performance [113].

Parts of the *Teams* effect may also reflect a Köhler-like mechanism: riders described feeling more accountable to the group and more attentive to shared timing, suggesting that team-based synchronization can motivate effort through responsibility for a collective outcome [40, 77, 121]. In our context, this is especially interesting because the shared task was not based on absolute performance, but on cadence-related synchronization, which is comparatively independent of fitness level. Beat-based team mechanics may therefore provide a more inclusive basis for social motivation in mixed-ability group classes than competition on power output or heart-rate values alone.

Importantly, potential Köhler-like motivation gains may not have been limited to the explicit *Teams* conditions. All four study conditions included group-wide Public Performance Feedback, which may already increase social awareness, comparison, and accountability. However, this was not entirely new to our participants, as the familiar Polar Club system used in their regular classes already displays participants' heart-rate percentages publicly on the wall. Our conditions therefore extended an existing form of public physiological feedback with cadence, scoring, game-like representations, and team mechanics rather than introducing public feedback from scratch. The team structure may thus have amplified an already social feedback situation, which may help explain why Social Setting produced selective rather than broad effects.

At the same time, the social effects were clearly ambivalent. Team modes were often experienced as motivating and more fun, but they were also described as socially stressful and as masking weaker individual performance. This ambivalence is also reflected in the rankings, where the *Single* variants tended to outperform the *Teams* variants overall. In our setting, *Teams* seems most valuable when the design goal is shared rhythm and group awareness [58, 127].

6.3 Why Some Effects Remained Selective: Moderators, Null Effects, and the Role of Heart Rate

A notable finding is that the robust condition effects were concentrated in pragmatics, hedonic quality, mental demand, flow, and synchronization, while motivation, enjoyment, perceived exertion, and heart-rate target adherence showed no equally strong and stable pattern. The qualitative data suggest that this is not because these aspects were unimportant, but because they were highly dependent on context and individual preference. Some riders appreciated gamification, others rejected it, and still others preferred team modes for motivation but single modes for focus. This interpretation is consistent with the critical gamification literature, which emphasizes that game mechanics do not inherently increase motivation or effort, but depend on contextual fit and on users' interpretations of the implemented mechanics [74, 129]. In addition, the field-study setup was novel, visually rich, and more elaborate than the participants' regular class routine, so all four variants may have benefited from a general novelty effect, while perceived exertion remained strongly shaped by the training plan, the instructor, and individual fitness.

A similar argument helps explain the null effects for heart-rate target adherence. Heart rate was already a familiar metric from Polar Club and reacts more slowly than cadence to short changes in exertion, making it less sensitive to moment-to-moment interaction design over short intervals. The interviews further suggest that many riders focused more strongly on cadence and beat than on exact heart-rate regulation when both had to be managed at the same time. This absence of condition-specific heart-rate effects is compatible with prior work showing that music and interaction design can alter subjective exercise experience even when physiological measures remain comparatively stable [103]. At the same time, heart rate remains important as a training- and safety-related anchor, especially in a high-intensity activity such as indoor cycling [26, 90]. Our results therefore suggest a division of labor between metrics: heart rate supports safe intensity regulation, whereas cadence and beat synchronization are more sensitive to the design of moment-to-moment interaction. In this sense, our system extends familiar heart-rate-centered practice and complements more gameful physiological regulation approaches such as Hein et al. [49].

The subgroup analyses further suggest that these effects may be moderated by rider characteristics. Participants under 40 years of age showed a more pronounced *Dashboard* versus *Game* pattern, and highly experienced riders showed clearer *Teams* effects on perceived beat synchronization. Although these subgroup results should be interpreted cautiously, they fit the interview evidence that rhythm ability, familiarity with riding to the beat, and comfort with social comparison vary strongly across riders.

6.4 Design Implications and Deployment

Taken together, the results suggest four main design implications for SportsHCI systems in co-located exercise. Although our deployment was situated in Spinning®, these implications address a broader class of co-located, rhythm-oriented sports systems in which physiological regulation, shared tempo, and public feedback are combined, such as rowing or dance-based exercise classes.

First, direct and readily interpretable feedback should serve as the baseline in high-intensity group training. In our study, the dashboard consistently supported pragmatic quality, lower mental demand, higher flow fluency, and better subjective and objective synchronization. This also matched the interview feedback, where the dashboard was repeatedly described as easier to understand and closer to the established class routine. Because indoor cycling is intense and benefits from close monitoring [90], retaining clear heart-rate visualization for both riders and instructors appears especially important [26].

Second, gameful feedback is best treated as an optional experience layer rather than a full replacement for direct performance displays. The *Game* conditions added variety, stimulation, and memorability, but their benefits depended on the readability of the mapping between game events and training state. Future game variants should therefore reduce the number of interpretation steps required under exertion, for example through clearer visual status indicators or more direct mappings from target adherence to game progress.

Third, social modes should be deployed selectively and can benefit from beat-based rather than absolute performance metrics. In our study, *Teams* primarily strengthened perceived rhythm and class synchrony rather than globally increasing motivation. This suggests value for rhythm-focused drills, warm-up segments, or occasional team sessions, but not necessarily as a constant default. Compared with competition on power output or heart-rate values, cadence-based mechanics may offer a more inclusive basis for social motivation in mixed-ability group classes. This relates to prior exertion-game work on balancing physical experiences across participants with different abilities [55, 82]: in our case, inclusiveness came from using target adherence and shared cadence as interaction resources that are less dependent on absolute fitness. If team-based modes are used, the design should also mitigate social stress, for example through softer comparison, more cooperative framing, or optional participation.

Fourth, music, instructor guidance, and class flow should be treated as core parts of the interaction design rather than background context. Participants repeatedly noted that synchronization depended on song characteristics, clear beats, and comprehensible tempo changes, which makes music-synchronized feedback a particularly promising design resource for co-located group training [59, 103]. At the same time, both participants and instructors emphasized that Spinning® is a co-located, instructor-led practice in which pacing, motivation, and social atmosphere are central. Systems for this context should therefore augment the class rather than replace it. This interpretation also resonates with prior work on shared physiological displays and collaborative cycling feedback, which suggests that real-time exercise data become especially valuable when they support dialogue, coordination, and social training processes [3, 112]. Such data may also support longer-term reflection and coaching, for example by tracking progress over time [25].

6.5 Limitations

This work has several limitations. First, the deployment was short-term and embedded into four classes at a single university sports club. The results therefore capture immediate use and early adaptation rather than longer-term changes in motivation or adherence.

Because all four conditions were experienced within a single class session, fatigue or carryover effects cannot be fully excluded, although the condition order was counterbalanced across the four classes to mitigate such influences. Second, both the full sample and the balanced analysis subset were dominated by relatively experienced Spinning® riders, which may limit generalization to less experienced or less fit populations. Third, practical issues likely influenced the experience independently of the conceptual condition differences, including jumping cadence values, visibility constraints in the room, and the readability of avatars and projections from different bike positions. Fourth, although we also collected HEXAD-related data [69, 110], the sample size with $N = 61$ was too small for a robust player-type analysis, even though the qualitative findings suggest substantial differences in preferences for gamification, competition, and self-focus. Fifth, all four study conditions included public group-wide feedback, and while all participants were already familiar with public heart-rate feedback through Polar Club, our design cannot isolate its motivational effect from the effects of game-like representation or team structure.

6.6 Implications and Future Work

A first next step is longitudinal and adaptive deployment. Repeated use over several weeks would allow future work to examine whether the dashboard remains the preferred baseline after novelty effects fade, whether riders learn to interpret the game feedback more fluently over time, and whether team-based modes become more attractive once users are familiar with the system. The present results also suggest that feedback style and social mode should not be fixed for everyone. Future systems could progressively introduce mechanics based on rider experience, rhythm ability, or preference, or allow instructors and riders to choose among modes depending on the class segment and training goal.

A second direction is to extend the game and social mechanics while preserving cognitive simplicity. Future work could explore richer cooperative tasks, role-based team play, rhythm challenges, or strategy elements [58]. Relatedly, shared rhythm, public feedback, and team mechanics could also be extended to distributed or hybrid training formats. However, such designs would need to account for network latency and for the possibility that part of the appeal of indoor cycling classes lies precisely in their co-located social character, despite the availability of connected platforms such as Peloton and Zwift [16, 48, 89, 130].

Finally, the design space explored here may extend beyond indoor cycling. The combination of heart-rate regulation, tempo- or cadence-based synchronization, and shared public feedback may also be relevant for other co-located, rhythm-oriented exercise formats such as rowing classes, treadmill-based group workouts, cross-trainers, dance-oriented exercise, or hybrid formats such as Zumba®, potentially supported by additional sensing through IMUs in watches, bracelets, or shoes. More broadly, our findings suggest that SportsHCI can benefit from treating shared timing not merely as a property of exercise, but as a design material for shaping interaction, coordination, and engagement across various co-located sports classes.

7 Conclusion

This paper presented an end-to-end system for music-synchronized group cycling that augments conventional indoor bikes with heart-rate, cadence, and braking-resistance sensing and couples these data to private and public feedback displays. Using this system, we investigated how *Feedback Style* and *Social Setting* shape user experience and synchronization in real Spinning® classes.

Across the findings, one conclusion stands out: extending familiar heart-rate feedback with cadence-based, music-synchronized feedback is a viable and valuable design resource for co-located group exercise. The representation of feedback mattered more than the social manipulation alone. *Dashboards* provided a robust default for intensive training by supporting pragmatic, low-effort interpretation, higher flow fluency, and better subjective and objective synchronization. *Games* added experiential value and variety, but required more interpretation under exertion. *Teams* primarily strengthened the feeling of shared rhythm.

Taken together, these findings suggest that indoor-cycling systems should not aim for a single universally best mode. Instead, they should support a repertoire of modes: dashboards as a reliable baseline, games as optional experience layers, and team mechanics for moments in which group awareness and synchrony are the design goal. More broadly, the results show that suitable gamification and social mechanics in group exercise depend on context, prior experience, and individual preferences. In this sense, our contribution is not only a deployable system and field study of music-synchronized group cycling, but also a design perspective for SportsHCI that treats shared timing as a resource for shaping interaction, coordination, and engagement.

Beyond indoor cycling, this design space may also be relevant for other co-located, rhythm-oriented exercise formats such as rowing classes, treadmill-based group workouts, cross-trainers, or dance-based exercise such as Zumba®, potentially supported by additional sensors such as IMUs in wearables. More broadly, our work highlights how heart-rate and cadence synchronization, music, and social feedback can be combined to create richer and more varied sports-class experiences while remaining compatible with instructor-led practice.

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A Appendix

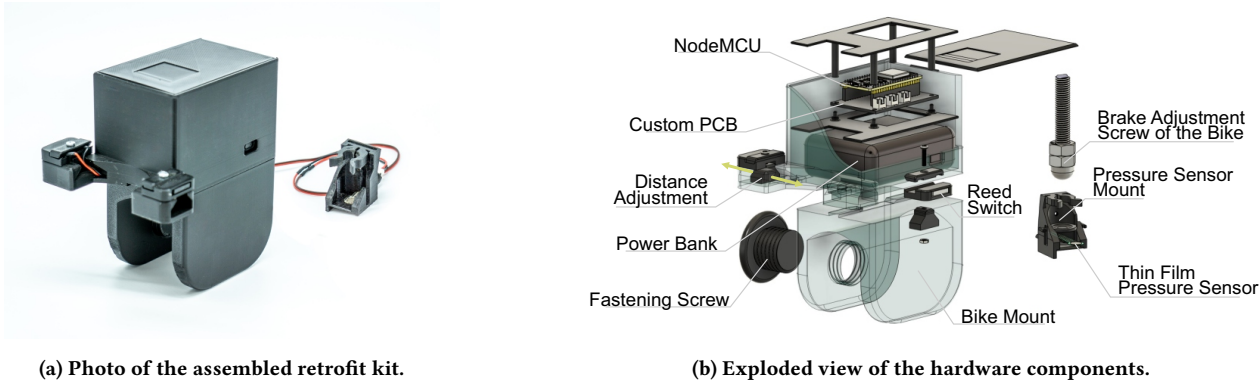


Figure 7: Detailed view of the retrofit hardware used to instrument the indoor cycling bikes. The kit consists of a 3D-printed housing containing the microcontroller, custom PCB, and power bank, adjustable reed-switch mounts for pedal-stroke detection, and a dedicated pressure-sensor mount attached to the brake adjustment screw.

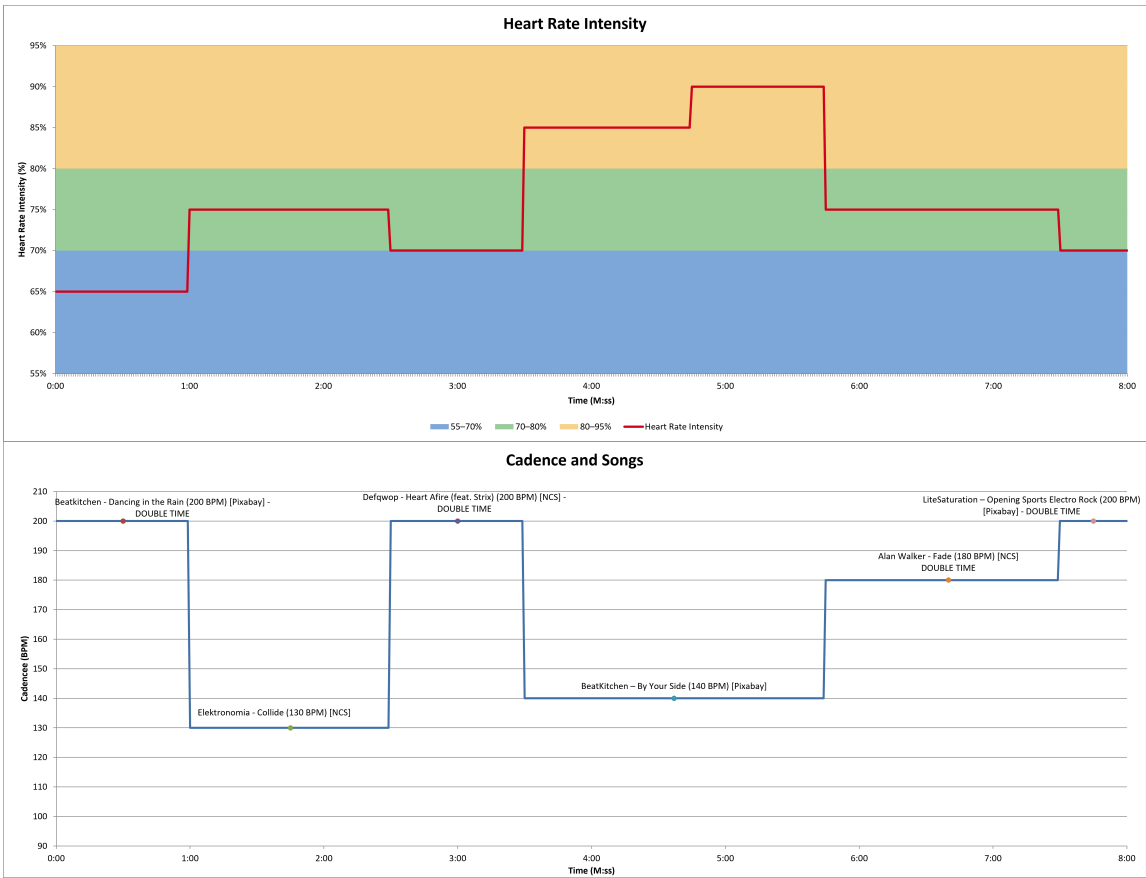


Figure 8: Training plan used in all four study conditions. The upper plot shows the target heart-rate intensity over an eight-minute session, and the lower plot shows the corresponding cadence targets and song sequence. The plan alternates between lower and higher intensity phases and includes several double-time sections for higher target cadences.

Table 1: Repeated-measures ANOVA results (within-subjects): all participants (subjective and objective measures, $N = 44$ participants, 4 repeated conditions per participant), $df = (1, 120)$.

DV	Effect	F	p	η_p^2	ES	Sig.
UEQ Pragmatic Quality						
	Social: Single vs. Teams	0.0077	.9300	0.0001	–	
	Feedback: Game vs. Dashboard	12.2971	.0006	0.0930	medium	***
	Social $\times$ Feedback	0.0202	.8873	0.0002	–	
UEQ Hedonic Quality						
	Social: Single vs. Teams	1.2125	.2730	0.0100	small	
	Feedback: Game vs. Dashboard	9.2719	.0029	0.0717	medium	**
	Social $\times$ Feedback	0.0015	.9694	< .0001	–	
NASA-TLX Mental Demand						
	Social: Single vs. Teams	0.2913	.5904	0.0024	–	
	Feedback: Game vs. Dashboard	9.9458	.0020	0.0765	medium	**
	Social $\times$ Feedback	0.3004	.5846	0.0025	–	
Flow Short Scale (Fluency)						
	Social: Single vs. Teams	0.0767	.7823	0.0006	–	
	Feedback: Game vs. Dashboard	6.7887	.0103	0.0535	small	*
	Social $\times$ Feedback	1.0857	.2995	0.0090	–	
Perceived Beat Synchrony						
	Social: Single vs. Teams	6.7610	.0105	0.0533	small	*
	Feedback: Game vs. Dashboard	4.6492	.0331	0.0373	small	*
	Social $\times$ Feedback	0.0571	.8115	0.0005	–	
Mean BPM Deviation from Group Mean						
	Social: Single vs. Teams	2.4387	.1210	0.0199	small	
	Feedback: Game vs. Dashboard	13.3251	.0004	0.0999	medium	***
	Social $\times$ Feedback	1.4594	.2294	0.0120	small	

Note. Significance: * $p < .05$, ** $p < .01$, *** $p < .001$, $^{\dagger}p < .10$. ES = qualitative effect-size category (as reported in the output).

Table 2: Pairwise contrasts for significant main effects (all participants).

DV	Contrast	Test
UEQ Pragmatic Quality	Dashboard vs. Game	$t(120) = 3.5067, p = .0006$
UEQ Hedonic Quality	Dashboard vs. Game	$t(120) = -3.0450, p = .0029$
NASA-TLX Mental Demand	Dashboard vs. Game	$t(120) = -3.1537, p = .0020$
Flow Short Scale (Fluency)	Dashboard vs. Game	$t(120) = 2.6055, p = .0103$
Perceived Beat Synchrony	Dashboard vs. Game	$t(120) = 2.1562, p = .0331$
Perceived Beat Synchrony	Teams vs. Single	$t(120) = 2.6002, p = .0105$
Mean BPM Deviation from Group Mean	Dashboard vs. Game	$t(120) = -3.6504, p = .0004$

Table 3: Repeated-measures ANOVA results (within-subjects): subgroup < 40 years (subjective and objective measures, $N = 28$ participants, 4 repeated conditions per participant), $df = (1, 78)$.

DV	Effect	F	p	η_p^2	ES	Sig.
UEQ Pragmatic Quality						
	Social: Single vs. Teams	0.2114	.6469	0.0027	–	
	Feedback: Game vs. Dashboard	14.4457	.0003	0.1563	large	***
	Social $\times$ Feedback	0.0126	.9108	0.0002	–	
UEQ Hedonic Quality						
	Social: Single vs. Teams	0.7211	.3984	0.0092	–	
	Feedback: Game vs. Dashboard	9.3734	.0030	0.1073	medium	**
	Social $\times$ Feedback	0.0881	.7674	0.0011	–	
NASA-TLX Mental Demand						
	Social: Single vs. Teams	0.2475	.6203	0.0032	–	
	Feedback: Game vs. Dashboard	5.9610	.0169	0.0710	medium	*
	Social $\times$ Feedback	0.0000	1.0000	0.0000	–	
Flow Short Scale (Fluency)						
	Social: Single vs. Teams	0.2142	.6448	0.0027	–	
	Feedback: Game vs. Dashboard	5.1605	.0259	0.0621	medium	*
	Social $\times$ Feedback	0.6279	.4305	0.0080	–	
Perceived Beat Synchrony						
	Social: Single vs. Teams	0.9230	.3397	0.0117	small	
	Feedback: Game vs. Dashboard	5.1888	.0255	0.0624	medium	*
	Social $\times$ Feedback	0.4281	.5148	0.0055	–	
Mean BPM Deviation from Group Mean						
	Social: Single vs. Teams	5.1171	.0265	0.0616	medium	*
	Feedback: Game vs. Dashboard	15.1808	.0002	0.1629	large	***
	Social $\times$ Feedback	1.3043	.2569	0.0164	small	
Mean BPM Deviation from Target						
	Social: Single vs. Teams	1.5481	.2171	0.0195	small	
	Feedback: Game vs. Dashboard	6.5916	.0122	0.0779	medium	*
	Social $\times$ Feedback	0.5239	.4713	0.0067	–	

Note. Significance: * $p < .05$, ** $p < .01$, *** $p < .001$, $p < .10$. ES = qualitative effect-size category (as reported in the output).

Table 4: Pairwise contrasts for significant main effects (subgroup < 40 years).

DV	Contrast	Test
UEQ Pragmatic Quality	Dashboard vs. Game	$t(78) = 3.8007, p = .0003$
UEQ Hedonic Quality	Dashboard vs. Game	$t(78) = -3.0616, p = .0030$
NASA-TLX Mental Demand	Dashboard vs. Game	$t(78) = -2.4415, p = .0169$
Flow Short Scale (Fluency)	Dashboard vs. Game	$t(78) = 2.2717, p = .0259$
Perceived Beat Synchrony	Dashboard vs. Game	$t(78) = 2.2779, p = .0255$
Mean BPM Deviation from Group Mean	Teams vs. Single	$t(78) = -2.2621, p = .0265$
Mean BPM Deviation from Group Mean	Dashboard vs. Game	$t(78) = -3.8963, p = .0002$
Mean BPM Deviation from Target	Dashboard vs. Game	$t(78) = -2.5674, p = .0122$

Table 5: Repeated-measures ANOVA results (within-subjects): Spinning®-experienced subgroup (subjective and objective measures, $N = 16$ participants, 4 repeated conditions per participant), $df = (1, 39)$.

DV	Effect	F	p	η_p^2	ES	Sig.
UEQ Pragmatic Quality						
	Social: Single vs. Teams	0.0329	.8570	0.0008	–	
	Feedback: Game vs. Dashboard	2.3593	.1326	0.0570	small	
	Social $\times$ Feedback	0.8241	.3695	0.0207	small	
UEQ Hedonic Quality						
	Social: Single vs. Teams	0.2440	.6241	0.0062	–	
	Feedback: Game vs. Dashboard	4.0161	.0520	0.0934	medium	.
	Social $\times$ Feedback	0.9971	.3242	0.0249	small	
NASA-TLX Mental Demand						
	Social: Single vs. Teams	3.6642	.0630	0.0859	medium	.
	Feedback: Game vs. Dashboard	1.7146	.1981	0.0421	small	
	Social $\times$ Feedback	2.6023	.1148	0.0626	medium	
Flow Short Scale (Fluency)						
	Social: Single vs. Teams	0.0953	.7592	0.0024	–	
	Feedback: Game vs. Dashboard	0.1893	.6659	0.0048	–	
	Social $\times$ Feedback	0.9285	.3412	0.0233	small	
Perceived Beat Synchrony						
	Social: Single vs. Teams	15.0911	.0004	0.2790	large	***
	Feedback: Game vs. Dashboard	2.4557	.1252	0.0592	small	
	Social $\times$ Feedback	1.4710	.2325	0.0363	small	
Mean BPM Deviation from Group Mean						
	Social: Single vs. Teams	3.6917	.0620	0.0865	medium	.
	Feedback: Game vs. Dashboard	4.4693	.0410	0.1028	medium	*
	Social $\times$ Feedback	1.5216	.2248	0.0376	small	

Note. Significance: * $p < .05$, ** $p < .01$, *** $p < .001$, · $p < .10$. ES = qualitative effect-size category (as reported in the output).

Table 6: Pairwise contrasts for significant main effects (Spinning®-experienced subgroup).

DV	Contrast	Test
Perceived Beat Synchrony	Teams vs. Single	$t(39) = 3.8847, p = .0004$
Mean BPM Deviation from Group Mean	Dashboard vs. Game	$t(39) = -2.1141, p = .0410$