UNIVERSITY OF TWENTE.

Faculty of Electrical Engineering, Mathematics & Computer Science

Proxies and Balancing for Shared Flow in Older Adult Cyclists

Laura Kahnt

M.Sc. Thesis
Interaction technology
April 2023

Graduation committee
prof. dr. P.J.M. Havinga - chair
M.R. Boot, MSc - daily supervisor
dr. D.B.W. Postma - external examiner

Pervasive Systems Group
Faculty of Electrical Engineering,
Mathematics and Computer Science
University of Twente
The Netherlands

Abstract

Cycling, a healthy and eco-friendly activity enjoyed by people of all ages and fitness levels, can be further encouraged by improving the cycling experience. The mental state of flow, characterized by complete absorption and engagement in an activity that matches one's skill level, is considered as the optimal experience in physical activity. While flow has mainly been studied in individual settings, it can also be experienced in groups and has been shown to be more enjoyable. However, differences in fitness levels among cyclists can make it difficult to experience shared flow. The motor of electric bicycles can help address these differences by providing more support to less-fit cyclists (positive balancing) or reducing support for fitter cyclists (negative balancing). The aim of this study was to identify directly measurable proxies for shared flow and examine the impact of positive and negative balancing on shared flow. To accomplish this, an experiment was conducted with pairs of older adult recreational cyclists, a group that the Dutch government actively encourages to cycle more. The collected data was analyzed using mixed-effects regression models. The results indicate that the relative position and cadence of cyclists could serve as directly measurable proxies for shared flow, while heart rate may not be as suitable. However, these findings may not be generalizable to other populations or contexts due to the limitations of this study. Furthermore, this study did not find a significant relationship between balancing and shared flow, though further analysis revealed some leads indicating negative balancing could be more suitable to induce shared flow than positive balancing. However, additional research is necessary before firm conclusions can be drawn on the effect of balancing on shared flow. To advance the field of study, future research should improve data collection and analysis methods, test with diverse populations, and incorporate additional physiological and neurological measures.

Keywords

Flow in cycling groups, Older adults, Electric bicycles, Balancing fitness levels

I. Improving the shared cycling experience

Cycling is a fantastic way to enjoy the outdoors, exercise, and have fun! It not only benefits cardiovascular health, reduces the risk of chronic illnesses, and promotes mental well-being but also is a low-impact activity suitable for people of all ages and fitness levels (Singh Thakur and Madhusudhana Babu, 2019). In addition, cycling has positive environmental effects by reducing carbon emissions, and it can promote social connections and community involvement through group rides and events (Pucher, 2012). Despite the significant benefits of cycling, previous research has primarily focused on the physical and economic factors (Pucher, 2012), neglecting the subjective experiences of cycling (Popan, 2020; Singleton, 2019; Spinney, 2009). The importance of enjoyment and fun in cycling has been identified as a significant motivator for individuals (Petosa and Holtz, 2013). Thus, understanding what contributes to a positive cycling experience is crucial for promoting cycling programs and interventions and encouraging more people to cycle for transportation, recreation, and exercise.

Flow is a mental state characterized by complete engagement and absorption in an activity that matches one's skill level (Csikszentmihalyi, 2014). It has been extensively studied as an indicator of optimal experience during exercise (Swann et al., 2022), with research showing that it can increase motivation (Schüler and Brunner, 2009) and adherence to exercise routines (Elbe et al., 2016). Existing research on flow during cycling primarily focuses on performance improvement rather than experience and is restricted to younger adults (Goddard et al., 2021). Additionally, research on flow has mostly been limited to individual flow experiences, while recent research has indicated that flow can also be shared among groups (Pels et al., 2018), potentially enhancing the enjoyment of exercise (Walker, 2010). Given the potential benefits of shared flow experiences and the lack of research in the context of cycling experience, particularly among older adults, further investigations are necessary to measure and enhance shared flow experiences in this population.

The focus of this study lies on the recreational cycling population within the older adult demographic for several reasons. Firstly, this group is a significant and growing population in the Netherlands (CBS Statistics Netherlands, 2022). Secondly, they are the most common users of electric bicycles in the country (Van Deemter et al., 2022). Lastly, the Dutch government is actively promoting cycling among the older adult population through national initiatives such as Cycleon (Rijksoverheid, n.d.). The study's findings have the potential to provide valuable insights into promoting cycling among the older adult population.

This study has two goals. The first goal is to identify directly measurable proxies for shared flow while cycling on electric bicycles. Although previous studies have used self-report questionnaires (Jackman et al., 2019), physiological measures (Tyagi et al., 2016; Wang and Hsu, 2014), and behavioral measures (Oliveira et al., 2021; Swann et al., 2012) to assess individual flow experiences, little research has been done to identify measurable proxies for shared flow experiences. The identification of such proxies would be particularly valuable in assessing cycling experience and developing interactive and adaptive systems, such as electric bicycles. The second goal is to enhance the experience of shared flow on the electric bicycle. Achieving shared flow in a group requires individuals to find a balance between their own skills and the level of challenge they face (Pels et al., 2018). This balance can be challenging to maintain, particularly when there are differences in fitness levels between cyclists. The electric bicycle motor has the potential to address this issue by providing more support for less fit cyclists, a method known as positive balancing, or reducing the support for fitter cyclists, known as negative balancing. These two balancing methods are expected to improve the shared flow experience.

To achieve this study's goals, the following two research questions were formulated:

1) Can position, heart rate, cadence, and/or a combination of these variables serve as measurable proxies for the experience of shared flow on the electric bicycle? If so, which features of these variables have a significant relationship with shared flow?
2) Does positive and/or negative balancing have a significant impact on the intensity of shared flow and/or the percentage of time spent in shared flow among recreational older adult cyclists, in comparison to no balancing?

The experimental design of this study involved a between-subjects approach, with ten pairs of older adult recreational cyclists riding electric bicycles. Both research questions were answered using mixed-effect regression models. Additionally, a literature review was conducted to establish a theoretical framework for the study.

II. Shared flow and balancing

This section explores the relationship between shared flow and balancing in recreational cycling. Initially, the concept of flow and its importance in the cycling experience is introduced. Afterward, the concept of shared flow is examined, along with its operationalization. Subsequently, different design approaches for balancing cyclists' fitness levels are presented. Finally, the hypotheses for the research questions of the study are presented.

A. The concept of flow

The concept of flow refers to a mental state characterized by full immersion and absorption in an activity that challenges an individual at a suitable level of skill, and is based on intrinsic motivation (Csikszentmihalyi, 1975; Fong et al., 2015). To conceptualize the experience of flow in exercise, Csikszentmihalyi's nine dimensions framework is often used (Csikszentmihalyi et al., 2005). An overview of the nine dimensions of flow and their descriptions can be found in Table I. For flow to occur, three conditions must be met: a balance between the the individual's skill level and perceived challenge, clear goals, and unambiguous feedback. The skill-challenge balance is considered the fundamental condition of flow (Fong et al., 2015). Autotelic experience, one of the six characteristics of flow, captures the intrinsic motivational aspect of flow, where the activity itself is rewarding. Research has shown that individuals with a more autotelic personality are better at finding their skill-challenge balance, and therefore more likely to experience flow in their daily lives (Tse et al., 2020). In this study, flow was defined using the visualization presented in Figure 1.

B. Flow within cycling experience

Flow shares multiple dimensions with theoretical models for cycling experience, such as the conceptualization of cycling experience by Liu and colleagues (Liu et al., 2021), which comprises the sensory, spatial, and social dimensions. The sensory dimension encompasses aspects such as skills/competencies and safety threats, which overlap with the first and sixth dimensions of flow: skill-challenge balance and sense of control. Pelzer (2012) also identified the intensity of cycling as a prominent factor in the cycling experience, linking it to the experience of flow. The feeling of safety is another recurring factor in frameworks for cycling experience (Van Hagen and Govers, 2019; Heinen et al., 2010). The spatial dimension includes the aspect of wayfinding, which could affect the merging of action and awareness and level of concentration while cycling, the second and fifth dimensions of flow. The influence of interactions with the geographic environment is also emphasized in the cycling experience frameworks of Pelzer (2012) and Heinen et al. (2010). The social dimension of cycling experience encompasses the interactions with other individuals while cycling. Interactions with cycling companions may influence the balance between the challenge and skill, while interactions with other road users may be more closely linked to the sense of control. Studies have demonstrated that experiencing flow in a social context contributes to a more positive experience (Walker, 2010). The social aspect of cycling experience is included in multiple cycling experience models (Heinen et al., 2010; Pelzer, 2012).

Table I: The nine dimensions of flow and their types and descriptions, adapted from Jackson and Marsh (1996)

Dimension	Type	Description
Challenge-skill balance	Condition	The individual perceives a balance between the challenge of the activity and his or her own skills
Clear goals	Condition	The goals in the activity are clearly defined for the individual
Unambiguous feedback	Condition	The individual receives immediate and clear feedback about succeeding his or her goal
Action-awareness merging	Characteristic	The individual is so involved in the activity that their actions become spontaneous or automatic
Concentration on task at hand	Characteristic	The individual is fully concentration on the task at hand
Sense of control	Characteristic	The individual experiences a sense of control, without actively attempting to exert control
Loss of self-consciousness	Characteristic	The sense of self becomes less prominent as the individual becomes fully absorbed and one with the activity
Transformation of time	Characteristic	The individual's perception of time slows down, speeds up or becomes irrelevant
Autotelic experience	Characteristic	The individual experiences the activity as intrinsically rewarding

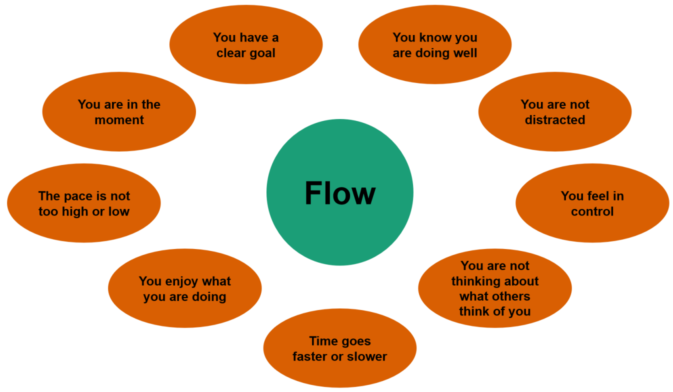


Figure 1: An adapted visualization of the nine dimensions of flow to better fit the context of cycling

C. Shared flow

In recent years, there has been an increasing recognition that flow is not limited to individual experiences, but also occurs in group settings (Pels et al., 2018). Shared flow emerges when a group engages in interdependent tasks and reaches a state of shared balance that is perceived to be within their capabilities (Salanova et al., 2014). Achieving shared balance in a group can be accomplished through various means, including balancing for competence based on group members' competences (Kiili and Perttula, 2010), mindset (Salanova et al., 2014), or behavior (Sawyer, 2003). This study focuses on competence balancing, which involves extending the skill-challenge balance necessary for individual flow to encompass all group members in order to attain shared flow (Pels et al., 2018).

Shared flow is characterized not only by a state of balance, but also by distinct social features that differentiate it from individual flow. Positive relationships and interactions among group members are essential for shared flow to occur (Pels et al., 2018). Individuals experiencing shared flow tend to synchronize their facial expressions, postures, and emotions, leading to physical and emotional synchronization (Salanova et al., 2014). Moreover, the flow experience may be transmitted from one group member to another, with individuals serving as agents of flow for each other. However, including these phenomena is out of scope for this study.

Shared flow can be defined in two ways: firstly, when all group members experience individual flow simultaneously (Csikszentmihalyi et al., 2005); and secondly, when all members of a group experience shared flow, including its unique social aspects (Hart and Di Blasi, 2015; Walker, 2010). In this study, shared flow is defined as the state where all individuals in a group experience individual flow simultaneously, as it is expected to be more challenging for the target group to recognize, understand, and remember experiencing shared flow, as opposed to individual flow.

D. Operationalizing shared flow

In order to make the subjective phenomenon of shared flow more tangible and measurable, operationalization is necessary. According to Goddard et al. (2021), flow can be measured in two ways: dispositional flow and state flow. Dispositional flow refers to the frequency or tendency of experiencing flow during a particular activity, while state flow pertains to the intensity of flow experienced during a particular activity. It is expected that dispositional and state flow can be extended to shared flow in this study, even though the existing literature on shared flow does not explicitly mention these concepts yet.

Considerably less research has been dedicated to operationalizing shared flow compared to individual flow. There are several approaches to operationalizing individual flow, including using self-report questionnaires (Jackman et al., 2019), physiological measures like heart rate variability (Tyagi et al., 2016) or electroencephalography (Katahira et al., 2018; Klasen et al., 2012; Nacke et al., 2011; Wang and Hsu, 2013), and behavioral measures like duration of time spent on a task (Oliveira et al., 2021) or level of performance (Swann et al., 2012). Existing studies on shared flow have mostly relied on qualitative research methods such as observations (Sawyer, 2003) and in-depth interviews (Hart and Di Blasi, 2015), as pointed out by Łucznik and May (2021). Although some researchers have attempted to operationalize shared flow by modifying individual flow measures (MacDonald et al., 2006; Salanova et al., 2014), these methods have limited ability to capture the dynamic nature of shared flow. Capturing the dynamics of shared flow is important as it allows for tracking the frequency, stability, and patterns of the experience (Łucznik and May, 2021). To address this issue, Łucznik and May (2021) developed a video-stimulated recall method called Flowi, which allows participants to mark video segments where they experienced shared flow and share their thoughts while watching the video. However, this approach is retrospective, dependent on the participants' interpretation of flow, and time-consuming. Furthermore, it cannot be integrated into real-time interactive and adaptive systems such as electric bicycles. Therefore, there is a need for directly measurable proxies for shared flow.

Directly measurable proxies are anticipated to aid researchers in evaluating and improving shared cycling experiences. Heart rate is a potential variable that could be used for this purpose, as it has been linked to the experience of flow during moderate levels of exertion (Tian et al., 2017). Similar levels of moderate exertion among cyclists may indicate shared flow. Moreover, an inverted U-shaped relationship has been observed between flow experience and sympathetic arousal, which is the body's fast response to stress (Peifer et al., 2022). Therefore, less changes in the heart rates of people cycling together may indicate less stress and greater shared flow. However, it is important to note that these studies were conducted in controlled stationary environments and that the relationship between heart rate and shared flow may differ in a more complex setting, such as cycling. Furthermore, heart rate has limitations as it can be influenced by many variables (Valentini and Parati, 2009) and may not be accurate during movement (Bent et al., 2020), and on-body sensors are often required. Despite these limitations, prior research has investigated the utilization of heart rate to balance shared experiences while exercising (Bayrak et al., 2017; Mueller et al., 2012; Sonne and Jensen, 2014; Stach, 2012). This current study will therefore further examine the correlation between heart rate and shared flow during cycling. An alternative variable to heart rate as a proxy for shared flow during cycling is cadence, which can be easily measured during the activity. Cadence refers to the number of revolutions per minute (RPM) of the pedals on a bicycle. It is a measure of how fast a cyclist is pedaling, and can affect the amount of power and efficiency of their cycling (Abbiss et al., 2009). Previous research has demonstrated that cadence is an important factor influencing perceived exertion (Abbiss et al., 2009) and pleasure (Kruschewsky et al., 2018), and that each cyclist has their preferred cadence (Lucía et al., 2001). Therefore, it is hypothesized that cadence could be a potential proxy for shared flow during cycling. Finally, the position of cyclists relative to each other may serve as a possible indicator of shared flow during recreational cycling. It is common for cyclists to ride side by side to facilitate social interaction. Thus, it is hypothesized that when one cyclist follows behind another, it may be due to the challenge exceeding their skill level, or external factors such as distractions on the road requiring additional attention or space.

E. Balancing for shared flow

The experience of shared flow is influenced by several factors, with one of the primary factors being the heterogeneity of skill levels within a group. In a cycling group, for example, cyclists may possess different levels of fitness. Some cyclists may experience an imbalance between their skills and the challenge at hand, because they are less fit than the other cyclists. Meanwhile, the fitter cyclists may also encounter an imbalance due to the challenge being too low for their skills. These imbalances between skill levels and challenges can make it difficult for individuals to attain individual flow, which can subsequently hinder the ability of the group to attain shared flow. To address this challenge, this study aims to establish a balance among group members based on their individual fitness levels.

Prior research has established that balancing for different levels of fitness can lead to more engaging experiences (Mueller et al., 2012). To facilitate such experiences, a comprehensive design framework has been proposed by Mueller et al. (2012), which comprises four dimensions:

- Measurement: This dimension involves different methods for measuring differences in abilities, such as estimations of skill based on age (Khoo et al., 2008) or self-reported skill level (Altimira et al., 2014), performance measures (Cechanowicz et al., 2014; Gerling et al., 2014; Stach and Graham, 2011), or exertion measures (Bayrak et al., 2017; Mueller et al., 2012; Sonne and Jensen, 2014; Stach, 2012). This study employs self-reported fitness level to measure differences in fitness levels.
- Presentation: This dimension involves the decision of whether to explicitly inform the participants about the balancing method before or during the activity or not. Research studies have provided inconclusive findings on whether explicit communication enhances the experience of an activity. Future studies may focus on investigating this matter. As keeping balancing entirely hidden from the participants was not feasible in this study, the fact that balancing would be applied with the motor of the electric bicycle was communicated, but not the specific method of balancing.
- Adjustment: This dimension involves determining how the balancing method is adjusted based on the input measured. Three methods are to be considered: static vs dynamic balancing (Bateman et al., 2011; Kraaijenbrink et al., 2009; Mueller et al., 2012; Stach, 2012), internal vs external balancing (Altimira et al., 2014), and positive vs negative balancing (Altimira et al., 2014, 2016; Bateman et al., 2011; Sonne and Jensen, 2014). Little research has been conducted on comparing the effects of these methods on the experience of exercise, especially within the context of cycling and shared flow. This study focused on exploring positive versus negative balancing, as it was most feasible and grounded in personal experiences. The motor support given to the less-fit cyclist was increased in positive balancing, while less motor support was given to the fitter cyclist in negative balancing. The balancing was applied statically, meaning the support did not change while cycling, and externally, as the motor of the electric bicycle was used.
- Control: This dimension involves determining who had control over the balancing mechanism. In this study, the researcher has control over the balancing because to answer the second research question an experimental approach was required. However, given the relevance of the sense of control in the nine dimensions framework for flow, future interventions may be better served by giving users control over the balancing.

F. Hypotheses

In this study, the first hypothesis is that position, heart rate, and cadence, either individually or in combination, can be used as measurable proxies for the experience of shared flow on electric bicycles. It was explained in Section II-D why these variables are believed to be correlated with shared flow. The average position during each thirty second interval was already anticipated to be correlated with shared flow, so no further features were extracted from position. Heart rate was measured directly, and heart rate features such as variance in heart rate per thirty-second interval, similarity in heart rate exertion per thirty-second interval, and difference in mean heart rate between thirty-second intervals were extracted. These features were expected to be correlated with shared flow since heart rate variance could indicate a more stable exertion level with fewer distractions, similar exertion levels among cyclists could suggest a shared positive experience, and a continuous mean heart rate could indicate that the cyclists are challenged according to their skills. From cadence, features such as mean, variance, and sum of zeros in each thirty-second interval, as well as the difference in mean cadence between intervals, were extracted. These cadence features were also expected to correlate with shared flow since a mean cadence of 60 to 80 rounds per minute may indicate an appropriate challenge level for the cyclist, less variability in cadence could suggest a better balance between skill and challenge with fewer distractions, and the continuity of cadence could indicate that the cyclists are being challenged according to their skills. Lastly, the sum of zeros in cadence shows when the cyclists stopped cycling, and fewer interruptions may indicate a higher likelihood of being in flow.

The hypothesis for the second research question is that both positive and negative balancing have a significant impact on the intensity of shared flow and the percentage of time spent in shared flow when there is a difference in fitness levels within a pair of cyclists. This hypothesis is based on the assumption that these balancing methods are effective in addressing the differences in fitness levels between cyclists.

III. Study design

In this study, a between-subjects design experiment was used to address two research questions with shared flow as the dependent variable. The first question was answered through a correlational analysis exploring the suitability of heart rate, cadence, and position as proxies for shared flow. The second question was addressed with an experimental approach investigating the impact of positive and negative balancing on shared flow, with balancing as the independent variable. Quantitative data, including heart rate, cadence, position, autotelic personality score, and self-reported shared flow, were collected during the experiment. Qualitative data was also collected to provide a more comprehensive understanding of the shared flow experience.

A. Participants

The study recruited twenty-one older adult individuals who were regular recreational cyclists. The recruitment process involved distributing screening materials to a variety of cycling and older adult associations. To be eligible for the study, participants had to be over 60 years of age, report an adequate fitness level, and have prior experience riding an electric bicycle. Participants were recruited in pairs, with ten males and eleven females participating, with an average age of 69.1 years. One male participant was paired with a female researcher for the pilot study, while the remaining twenty participants were recruited in pairs with pre-existing social relationships, either as friends (N = 2) or partners (N = 8). Out of these ten pairs, nine consisted of one male and one female participant, while one pair comprised of two females. Three pairs were evenly matched in terms of fitness level, while the remaining eight, including the pilot pair, had varying levels of fitness. These fitness levels were determined by self-report. As an incentive, each pair received two gifts, a towel and socks, from the University of Twente, for participating in the 2.5-hour experiment.

The participants reported varying levels of experience cycling with others, with 38.1% cycling daily, 47.6% cycling weekly, and 14.3% cycling monthly. Their experience with cycling on electric bicycles was for 42.9% cycling daily, 38.1% cycling weekly, 14.3% cycling monthly, and 4.8% cycling less than once a month. The study found that on average, the participants had an autotelic personality score of 3.78 (with a standard deviation of 0.33) on a Likert-scale from 1 (strongly agree) to 5 (strongly disagree). Eventually, the data from the pair of two females were excluded from the analysis for both research questions due to motor support malfunctioning during their experiment.

B. Setting, conditions and confounding variables

The study involved pairs of participants who cycled three rounds on Batavus Fonk electric bicycles under three different conditions. The bicycles were equipped with a cadence-based motor support system, which is considered less intuitive than the more commonly used torque-based support system in modern electric bicycles. The motor support had five levels. The three conditions were: no balancing, positive balancing, and negative balancing. To create these conditions, the motor support level of each bicycle was set to a fixed level by the researcher prior to each round. The specific motor support levels the participants received in each condition can be found in Table II. To ensure that the participants were unaware of the specific condition they were assigned to, the motor support level was masked with a paper over the interface.

Table II: The motor support levels given to the fitter and less fit participants based on the type of balancing applied

	No	Positive	Negative
Fitter participant	3	3	1
Less fit participant	3	5	3

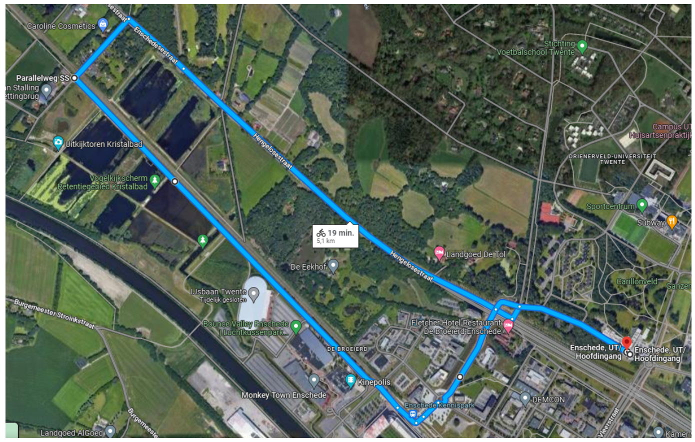


Figure 2: The cycling route used in the experiment, which started and ended at the location indicated by the red marker

The cycling route, depicted in Figure 2, was designed to be approximately five kilometers long and included four turns, with one crossing an intersection with traffic lights and one crossing a high-speed road without traffic lights. The route was designed to minimize the number of turns to reduce the participants' need to navigate, as this was expected to negatively affect their flow experience. This expectation was supported by the participants' comments at the end of the experiment. The majority of the route consisted of low-traffic, separate bicycle paths to ensure safety. Each pair of participants completed the route three times, with round times ranging from 13.5 to 18.5 minutes and an average of 14 minutes. The length of the route was deemed sufficient for flow to occur, as previous research has shown that flow can be induced in physical activities lasting less than 10 minutes (Lee and Payne, 2016; Łucznik and May, 2021; Thin et al., 2011). According to participant feedback, they enjoyed the route overall, although some participants reported being somewhat distracted by route navigation during the first round, and some reported feeling slightly bored during the third round. Future research should take these observations into consideration when designing a cycling route for an experiment.

To minimize the influence of several confounding variables, the study employed various measures as shown in Table III. The recruitment of participants helped to minimize some of these variables, while others were accounted for in the experimental procedure. In addition, to reduce the potential carryover effects of fatigue, the order of conditions was randomized for each pair of participants and a minimum rest period of 15 minutes was also provided between rounds during data collection for the shared flow experience. Further information about the experiment procedure is provided in Section III-F.

C. Operationalization of shared flow

In this study, two methods were used to operationalize shared flow. The first method, which was developed specifically for this study, drew on techniques from research conducted by Łucznik and May (2021) and aimed to retrospectively capture how the experience of shared flow changed over the duration of a cycling round. For this method, participants were first introduced to flow with the visual representation shown in Figure 1. The dimensions were worded in a manner that allowed participants to identify their flow experiences during their cycling rounds. Given the difficulty participants may have recalling when they

Table III: The confounding variables that influence the experience of shared flow

Confounding variable	Design approach to minimize the influence
Age	All participants were between 61 and 78 years old
Gender	All pairs consisted of one female and one male participant
Culture	All pairs originated from the same culture
Time	The conditions were randomized in order
Perceived safety	All participants were experienced in cycling on electric bicycles and in pairs
Social experience	All pairs had an existing relationship, either as friends or partners
Spatial experience	All pairs cycled the same route three times
Equipment	All pairs rode the same two bicycles
Weather	All pairs cycled in neutral, good or very good weather conditions (by self-report)

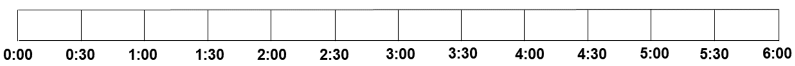


Figure 3: A partial view of the timeline for flow completed by each participant after each cycling round

experienced flow, video-stimulated recall was used to support their recollection. During the video-stimulated recall, participants completed a timeline of their cycling round, indicating 'yes,' 'no,' or 'maybe' options for flow in each thirty-second interval using green, red, and orange colors (see Figure 3). Shared flow was operationalized as being present when both participants indicated experiencing flow simultaneously.

The second method used to operationalize shared flow in this study involved a self-report questionnaire. An adapted version of the Shared Flow Scale (SFS) was used, which was originally derived from the Spanish version of Jackson and Marsh's Dispositional Flow Scale (Jackson and Marsh, 1996). The SFS was later adapted by García Calvo et al. (2008) and developed by Zumeta et al. (2013). The SFS measures nine dimensions of flow using 27 items with a Likert-scale range from 1 (not at all) to 7 (very much). To make the scale suitable for the cycling context and target group, one item per dimension was selected, and the first dimension's item was customized to cycling (see Appendix A). The response scale was also modified to range from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was translated into Dutch to match the language proficiency of the participants. Participants responded to the questionnaire individually, and a shared flow outcome for each pair was computed by averaging the questionnaire results from both participants.

D. *Data collection*

In this study, various methods were used to collect data, as summarized in Table IV and described in detail below. Data was collected both before the start of the cycling rounds and during and after each cycling round.

Before the cycling rounds started, the Autotelic Personality Questionnaire, developed by Tse et al. (2020), was administered to assess each participant's level of autotelic personality. This questionnaire was used as a measure to account for differences in proneness to experience flow between participants.

During the cycling rounds position, heart rate and cadence data were collected. The heart rate was recorded using an Empatica E4 wristband on the participant's preferred wrist. The E4 wristband derived the heart rate data from the photoplethysmogram sensor at a sampling rate of 64 Hz. The internal algorithm of the E4 wristband was used to estimate the heart rate for every second, resulting in a sampling rate of 1 Hz for analysis. The data was stored initially in the internal memory and subsequently uploaded to the Empatica cloud-based repository.

The participant's cadence was recorded using the Wahoo RPM bike cadence sensor. This sensor was attached to the bicycle crank and connected to the Wahoo Fitness app on a smartphone mounted on the bicycle via Bluetooth. The cadence sensor measured with a sampling rate of 1 Hz.

The position of the participants was determined through video analysis (see Figure 4 for a simplified visualization). This involved detecting the position of a Quick Response (QR) code on the side of one of the bicycles, using footage obtained from a GoPro Hero 5 action camera attached to the carrier of the other bicycle (see Figure 5). The camera was configured with a frame rate of thirty frames per second and a screen resolution of 2704x1520, with a linear field of view to minimize barrel distortion. Prior to conducting the experiment, multiple rounds of testing were performed to optimize the determination of the participants' relative position. Various sampling rates were tested to identify the lowest possible rate that would not significantly affect the recognition rate of the QR code. Additionally, various sizes and positions of the QR code were tested to determine the optimal configuration for recognition. The optimization process was terminated when the recognition rate of the QR code during cycling next to each other reached around two-thirds of the total frames.

After each cycling round, the participants reported their shared flow experience using two different operationalizations. The first operationalization involved completing a timeline of their experience of flow during the cycling round, which was

Table IV: Overview of the data collection methods used in this study.

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

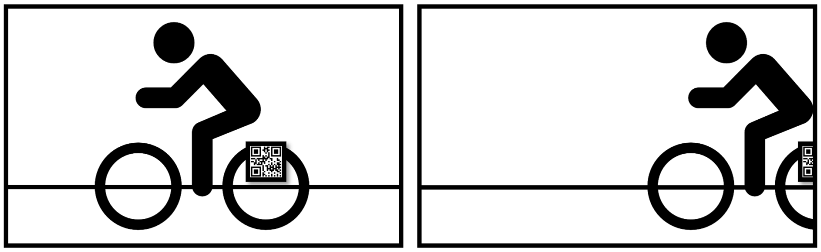
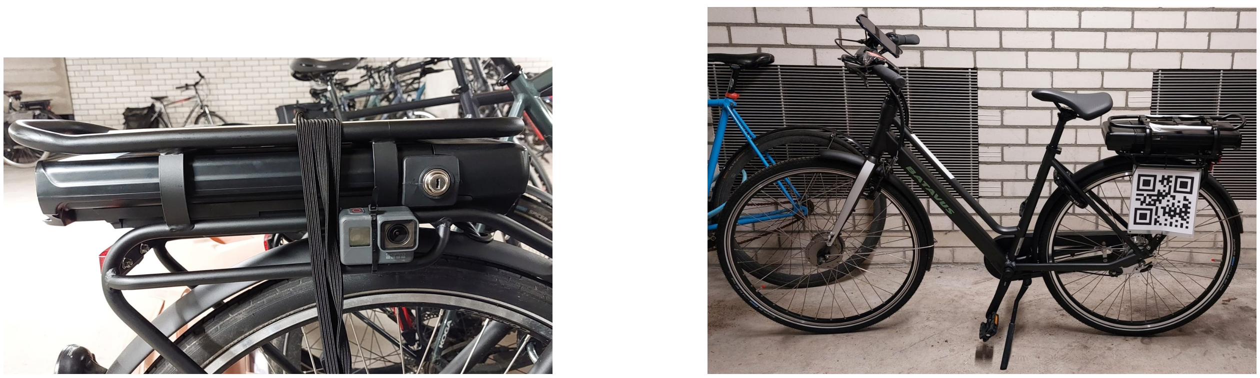


Figure 4: A simplified visualisation of how the participants' position was determined. In the left image, the participants were cycling next to each other, while in the right side they were not.



(a) The action camera is mounted to the side of the carrier on one bicycle

(b) The QR code is mounted to the side of the carrier on the other bicycle

Figure 5: The hardware set-up for measuring position

displayed in Figure 3. Using this timeline, the percentage of time that each pair spent in shared flow was calculated. The second operationalization of shared flow involved a self-report questionnaire that asked participants to rate their experience of shared flow during the cycling round. An adapted version of the Shared Flow Scale was used for this purpose (see Appendix A). Additionally, the participants graded their experience of the weather on a Likert-scale from 1 (very bad) to 5 (very good).

E. Ethical approval

This study obtained ethical approval from the Computer & Information Sciences Ethics Committee of the University of Twente, with application number 220017. All participants provided written, informed consent after receiving an information letter by email and attending a briefing session, during which they were verbally informed about the experiment.

F. Procedure

The participants were introduced to the experiment in a relaxed and informal setting at the canteen of the University of Twente. Having received an information letter beforehand, the introduction was kept brief. The introduction began by inquiring about the participants' comprehension of flow, and any misunderstandings that arose were addressed. The researcher then showed the visualization of flow used in this study (Figure 1) and explained that flow was characterized by experiencing multiple (not necessarily all) subdimensions simultaneously. To ensure the participants understood this study's definition of flow correctly, they were then asked to describe an experience of flow in their daily life. After the introduction, written informed consent and demographic information were collected. They also completed the Autotelic Personality Questionnaire (Tse et al., 2020) and self-reported their fitness levels. If participants reported similar fitness levels, the fitter individual was determined by their preferred motor support. The motor support of the bicycles was adjusted for each round based on the participants' fitness levels (see Table II). The participants were then instructed to wear the heart rate wristband, which was immediately turned on by the researcher. Subsequently, the timeline for flow (Figure 3), along with the adapted Shared Flow Scale (Appendix A), were explained so that the participants knew what to expect after each cycling round.

Before the cycling rounds began, each participant's bicycle seat and handlebar height were adjusted to their preferred settings. Then, each participant completed a 200-meter practice round to become accustomed to the bike. After both participants finished their practice round, the cadence sensor, smartphone camera, and action camera were turned on, and the first round began. The direction of their round was predetermined by simple randomization.

Once the cycling round was completed, the video recordings were stopped, and cadence data collection was paused. The pair then entered the building with the researcher to complete the timeline for flow using video recall. The researcher guided the participants in reviewing the recording within five minutes of finishing each cycling round. The participants vocalized their thoughts while completing the timeline, and the researcher recorded their remarks. The adapted Shared Flow Scale was also completed. The whole process was repeated two more times, with the cycling direction changing each time.

After the cycling rounds were finished, a short semi-structured interview was conducted with each pair. The participants were asked how they experienced the different rounds, what caused them to enter and exit a state of flow, and how they would have experienced the experiment differently if they participated alone. Following the interview, the participants were debriefed.

G. Pre-processing and feature selection

After data collection, an anonymous identifier was assigned to each pair's data. The data from the GoPro action camera, Empatica E4, and Wahoo RPM bike cadence sensor were pre-processed using Python programming language (Van Rossum and Drake, 2009). Synchronizing the data sources was the initial pre-processing step. Since the action camera was switched on and off at the start and end of each cycling round, no additional processing was required for this sensor. However, since there were no timestamps in the footage of the action camera and the heart rate and cadence sensors were not activated at the exact start and end times of each round, the start and end times for each round had to be manually identified. Both the heart rate and cadence sensor data contained Unix time. To determine the start and end times, the cadence data was employed. The start time was determined at the moment the cadence of both participants was no longer zero, while the end time was identified when both participants had a cadence of zero that remained constant. The estimated error margin for these times was approximately fifteen seconds. The cycling session was then divided into thirty-second intervals, which is in line with the output from the video-stimulated recall for shared flow.

The relative position of the participants was determined from the video footage captured by the GoPro Hero 5 action camera. Unlike heart rate and cadence, no additional features were extracted from the position data. The following processing steps were taken to determine the participants' position per interval:

1) The sampling rate was reduced from thirty frames per second to five frames per second for computational efficiency.
2) The OpenCV library (Bradski, 2000) was utilized in conjunction with the pyzbar library (Natural History Museum, 2021) to detect the position of the QR code in each frame. Successful identification of the QR code resulted in a value of 1, indicating that the participants were cycling next to each other. If the QR code was not recognized in a frame, a missing data point was generated, indicating that the position was uncertain due to the QR code's absence in the frame or the code's inability to identify it caused by factors such as lighting or an angled view.
3) The participants' average position was calculated per second by averaging the positions from every five frames while excluding the missing data points.
4) Missing data points for seconds were interpolated through padding, which involved copying the last available value. Interpolation was limited to a maximum of five seconds at a time.
5) Any remaining missing data points were labeled as 0, indicating that the participants were not cycling next to each other.
6) Lastly, a mode calculation was performed on all position values within each thirty-second interval, resulting in a single position value per interval.

The following three features were extracted from the participants' heart rate data for each thirty-second interval, using the formulas presented in Appendix B:

- Mean variance in heart rate: This feature was calculated by first computing the heart rate variance per participant using the pandas library (McKinney, 2010), and then taking the average of these values over the participants for each interval.
- Mean change in heart rate: The second feature was calculated by determining the mean heart rate of each participant in each interval using the pandas library, and then subtracting the mean heart rate of the participant's previous interval. After the subtraction, the absolute value was taken and the resulting values were averaged over both participants.
- Similarity in heart rate exertion: This was a nominal feature that depended on two conditions. First, it was determined whether the participants' relative heart rates were similar. The relative heart rate of each participant per interval was calculated by dividing their mean heart rate by their maximum heart rate, which was determined using a formula based on the research of Nes et al. (2013). The similarity between the participants' relative heart rates in an interval was determined by dividing the relative heart rates, and was considered true if the resulting value was between 0.85 and 1.15. Second, it was determined whether both participants were in heart rate zone one. This condition was considered true if both participants' relative heart rates were under 60% (Muangsrinoon and Boonbrahm, 2017).

The following four features were extracted from the participants' cadence data for each thirty-second interval, using the formulas presented in Appendix B:

- Mean cadence: The mean cadence of the participants in each interval was calculated using the pandas library. The mean cadence was converted to a nominal variable with a value of 1 if it was between 60 and 80 rotations per minute and 0 otherwise.

- Mean variance in cadence: This feature was calculated by first computing the variance in cadence per participant using the pandas library, and then taking the average of these values over the participants for each interval. The mean variance was then transformed into a nominal variable with a value of 1 if it was below 150 and 0 otherwise.
- Mean change in cadence: The mean change in cadence between the current and previous interval was determined by calculating the mean cadence of each participant in each interval using the pandas library, and then subtracting the mean cadence of the participant's previous interval. After the subtraction, the absolute value was taken and the resulting values were averaged over both participants. This feature was then transformed into a nominal variable with a value of 1 if it was below 15 and 0 otherwise.
- Mean sum of zeros in cadence: This feature was computed by counting the sum of zeros for each participant in each interval using the pandas library and then taking the average over both participants. Afterwards, the mean sum of zeros was transformed into a nominal variable with a value of 1 if it was less than 3 and 0 otherwise.

H. Statistical analysis of proxies for shared flow

A correlational analysis was conducted to examine the relationship between shared flow and fixed effects, including position, heart rate features, and cadence features. The autotelic personality score was also added to the fixed effects structure, as individuals with higher scores are more likely to experience flow (Tse et al., 2020). The variables included in the analysis are summarized in Table V. To account for multiple measurements taken from each pair, a mixed-effects logistic regression model was utilized with pair as a random effect. These kind of models have been used in cycling research studies before (Krizek et al., 2005; Nasri et al., 2020; Park et al., 2020). By taking into account both fixed and random effects, these models allow individualized fits to the data without loss of statistical power. A warning of confounding or overfitting is issued if the data quality is too poor or the dataset is too small. While other models such as tree-based models or machine learning combined with clustering algorithms may have performed better on this dataset, they were not considered within the scope of this study.

In the experiment, 949 thirty-second interval datapoints during twenty-seven cycling rounds conducted by nine pairs under randomized conditions (positive, negative, and no balancing) were collected. Missing and unreliable data had to be addressed before proceeding with the statistical analysis. Inconsistent cadence data and missing heart rate or cadence data in successive intervals were observed in some rounds, making comparison of statistical models unreliable. The inconsistent cadence data was identified by one cyclist having minutes of mean cadence zero while the other cyclist had significantly higher cadence. This occurred multiple times with the same bicycle, possibly due to a faulty or poorly attached cadence sensor. Including this data would have led to unreliable results. Therefore, only data from sixteen cycling rounds from seven pairs with complete and reliable data, totaling 468 datapoints, were included in the analysis. Prior to conducting the mixed-effects regression in Rstudio (R Core Team, 2022), an initial investigation was conducted to explore the potential of position, heart rate, and cadence as proxies for shared flow by analyzing their distribution during shared flow and no shared flow cycling experiences.

The collected data were analyzed using the glmer-function of the lme4 package (Bates et al., 2015) in Rstudio. The analysis began with an intercept-only model, and then fixed effects were added in a forward step-wise manner, including interactions between the fixed effects. To ensure that multicollinearity between fixed effects was not an issue, it was checked and found to be consistently below 0.7. The random effects pair, balancing type, and difference in fitness level were included to account for variability, but only as a random intercept, and not random slope, to avoid overfitting. Variables, whether fixed or random, were included in the model if they were significant (p-value$<$0.05) and if their addition lowered the Akaike Information Criterion (AIC) by at least 2.0. The analysis of the mixed-effects logistic regression model was concluded when no further improvement could be achieved. Subsequently, the effect size of each significant fixed effect was determined by computing the Odds Ratio (OR) from their estimated coefficient.

I. Statistical analysis of balancing for shared flow

The aim of the statistical analysis of balancing for shared flow was to investigate the effects of positive and negative balancing on the intensity and percentage of time spent in shared flow, compared to no balancing. To conduct this analysis, the collected data was first divided into two groups based on the fitness levels of the pairs, with similar and differing levels. From these two groups, only the six pairs that reported differing fitness levels were included in the analysis. Each of these pairs cycled three rounds with different balancing conditions, resulting in eighteen data points for analysis. Each data point represented one cycling round and included information about the pair, the type of balancing, the intensity of shared flow experienced in the round, and the percentage of time the pair spent in shared flow in the round.

The shared flow data was evaluated for distribution, outliers, and variances using Python. The normality of the data was tested with a Shapiro-Wilk test using the scipy library (Virtanen et al., 2020), where the null hypothesis was that the data is normally distributed. To identify any outliers, boxplots were created using the seaborn library (Waskom, 2021). Additionally, Levene's test was employed to examine the variance between the types of balancing, using the scipy library. The null hypothesis of Levene's test was that the variances are equal. As two outliers were observed in the percentage of time spent in shared

Table V: An overview of the variables in this study, including their types and definitions

Variable	Type	Definition
Shared flow	Dependent (nominal)	Indicates whether the participants are in shared flow 1: both participants are experiencing individual flow 0: only one or neither of the participants is experiencing individual flow
Position	Fixed effect (nominal)	Indicates whether the participants are cycling next to each other 1: the QR code is recognized in the frame of the action camera footage 0: the QR code is not present or unrecognizable in the frame of the action camera footage
Mean variance in heart rate	Fixed effect (continous)	The mean variance of heart rate, averaged over both participants
Mean change in heart rate	Fixed effect (continuous)	The absolute change in mean heart rate between the current and previous interval, averaged over both participants
Similarity in heart rate exertion	Fixed effect (nominal)	Indicates whether the relative heart rates of both participants are similar and both participants are in heart rate zone 1 1: the ratio of relative heart rates is between 0.85 and 1.15 and the relative heart rates of the participants are both below 60% 0: the ratio of relative heart rates is not between 0.85 and 1.15 or either of the relative heart rates of the participants is above 60%
Mean cadence	Fixed effect (nominal)	Indicates whether the mean cadence, averaged over both participants, is in between 60 and 80 rotations per minute 1: the mean cadence is in between 60 and 80 rotations per minute 0: the mean cadence falls outside the range of 60 to 80 rotations per minute
Mean variance in cadence	Fixed effect (nominal)	Indicates whether the variance of cadence, averaged over both participants, is low or high 1: the mean variance of cadence is below 150 0: the mean variance of cadence is 150 or higher
Mean change in cadence	Fixed effect (nominal)	Indicates whether the change in cadence between the current and previous interval, averaged over both participants is low or high 1: the absolute mean change in cadence is below 15 0: the absolute mean change in cadence is 15 or higher
Mean sum of zeros in cadence	Fixed effect (nominal)	Indicates whether the sum of zeros in cadence, averaged over both participants, is low or high 1: the mean sum of zeros in cadence is below 3 0: the mean sum of zeros in cadence is 3 or higher
Autotelic personality score	Fixed effect (ordinal)	Indicates the participants' proneness to flow on a scale from 1 to 5
Pair	Random effect (discrete)	The pair the participants are in (total of 10 pairs)
Balancing type	Random effect (discrete)	The balancing type applied to the participants 2: positive balancing 1: negative balancing 0: no balancing
Difference in fitness level	Random effect (nominal)	Indicates whether there is a difference in fitness level within the pair 1: the participants have different fitness levels 0: the participants do not have different fitness levels

flow data, simpler statistical models like repeated measures analysis of variance could not be used. Therefore, mixed-effects logistic regression analysis was conducted.

Two mixed-effects linear regression models were fitted using the lmer function of the lme4 package in Rstudio. One model had the intensity of shared flow as the dependent variable, while the other had the percentage of time spent in shared flow. The main fixed effect of interest was the balancing type, and the autotelic personality score was added to the fixed structure as it was hypothesized to have a direct influence on the shared flow experience. The interaction effect between the fixed effects was also examined. Multicollinearity between fixed effects was checked and found to be below 0.7. To account for the multiple measurements per pair, the analysis included pair as a random intercept. The significance of the relationship between balancing and shared flow was evaluated using the p-values (<0.05) obtained from the models.

An additional analysis was carried out to investigate the influence of balancing on the potential proxies for shared flow identified in the first research question. In case the analysis revealed no substantial effect, it could potentially account for the absence of the impact of balancing on the shared flow experience observed in this study.

IV. Results

The result section of this study is organized into three main parts. The first section presents the distribution of the data, followed by the findings related to the first research question on proxies for shared flow. The final section reports the results of the second research question, which focuses on balancing for shared flow.

A. Data distribution

The collected data was initially visualized by creating distributions of the position, heart rate, and cadence data for the two categories (yes/no) of shared flow before further analysis was conducted. The purpose of this was to provide an initial indication of the potential of these variables to act as proxies for shared flow. Although the distributions of all features of heart rate and cadence were analyzed, only the means are presented in Figures 7 and 8, respectively, as the same conclusions could be drawn from these. Figure 6 shows that the position of the cyclists is more often next to each other during shared flow, suggesting position could be a proxy for shared flow. Figure 7 suggests that heart rate may not be a suitable proxy for flow as no observable difference was found in the absence and presence of shared flow. Meanwhile, Figure 8 implies that cadence could serve as a proxy for shared flow since it exhibited different distributions in shared flow and no shared flow.

The pairs' intensity of shared flow and percentage of time spent in shared flow were analyzed and visually represented to create an understanding of the data for the second research question. As shown in Figure 9, the pairs reported experiencing shared flow with an intensity of at least 3.4 out of 5.0 in all rounds. On the other hand, Figure 10 reveals that there was more variation in the time spent in shared flow, with 50% of pairs spending between around 60% and 80% of their time in shared flow, and two outliers at around 22%. Normality tests were conducted, and the null hypothesis was not rejected for both intensity (p-value = 0.796) and percentage of time (p-value = 0.086) at a significance level of 0.05, indicating that both measures can be considered normally distributed. Furthermore, Levene's test was applied to test the equality of variances across balancing types, and the null hypotheses were not rejected for both intensity (p-value = 0.781) and percentage of time (p-value = 0.301) at a significance level of 0.05, suggesting that the variances are equal for both measures across balancing types.

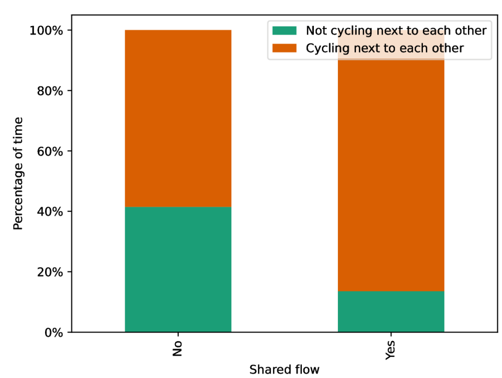


Figure 6: The percentage of time that pairs spent cycling next to each other during periods of shared flow and absence of shared flow

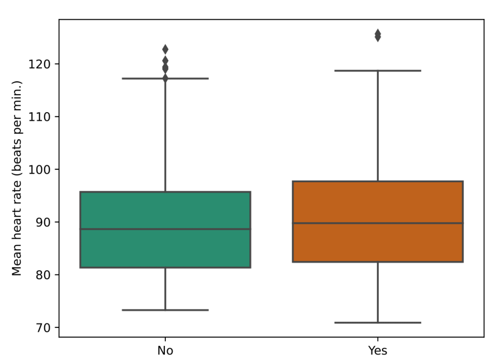


Figure 7: A comparison of the mean heart rate of pairs during periods of shared flow and absence of shared flow

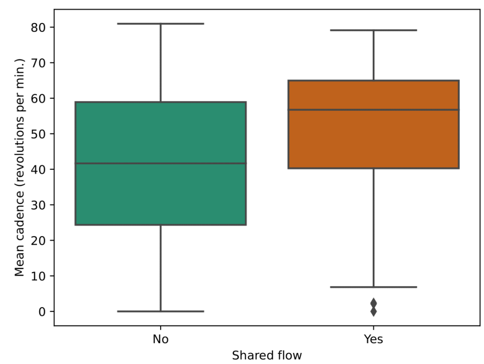


Figure 8: A comparison of the mean cadence of pairs during periods of shared flow and absence of shared flow

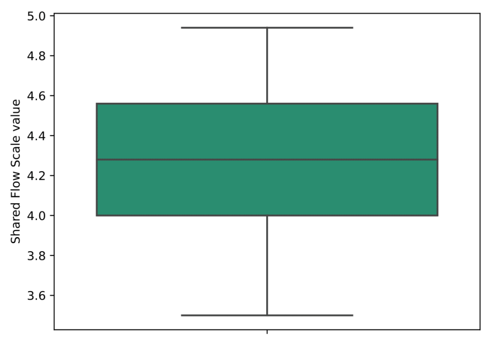


Figure 9: A boxplot displaying the intensity of shared flow experienced by all pairs across all rounds

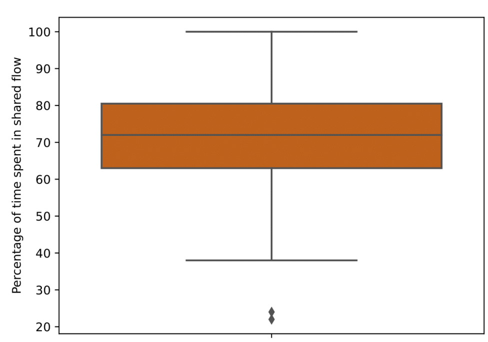


Figure 10: A boxplot displaying the time spent in shared flow by all pairs across all rounds

B. Proxies for shared flow

As mentioned before, mixed-effects logistic regression was used to analyze the collected data (see Figure V for an overview of all variables that were considered). The significant effects of the final model are presented in Table VI, where SE refers to the standard error and CI indicates the confidence interval. Position, mean change in cadence, mean sum of zeros in cadence, and autotelic personality score were found to have significant effects on the probability of experiencing shared flow. Specifically, shared flow was more likely to occur when participants cycled next to each other, maintained a continuous cycling cadence over time, experienced less interruptions in their cadence, and had a higher autotelic personality score.

Specifically, position had a pronounced and significant effect on the likelihood of experiencing shared flow. Participants cycling next to each other had a 5.10 times greater likelihood of experiencing shared flow compared to those not cycling next to each other, after controlling for other predictors in the model. This effect size can be interpreted as large, as an OR of 3 or greater indicates a large effect size.

Additionally, mean change in cadence was found to hold a significant relationship with shared flow. When the mean change in cadence between two thirty second intervals was less than fifteen RPM, the probability of shared flow increased by a factor of 2.18, indicating a moderate effect size.

Furthermore, sum of zeros in cadence had a significant influence on the experience of shared flow. When participants cycled without interruption (stopped for maximally three seconds per thirty seconds), the odds of experiencing shared flow increased by a factor of 1.69, indicating a small effect size.

Finally, autotelic personality score was also found to be a significant predictor of shared flow. A one-unit increase in autotelic personality score resulted in a factor increase of 1.53 in the probability of shared flow, indicating a small effect size.

The fixed effects did not account for all variance in the probability of experiencing shared flow, as reflected by the random intercepts (refer to Table VII). Among the sources of variance, the difference in fitness level within a pair was found to be the most explanatory. This was followed by balancing type and, lastly, the pair from which the data originated.

C. Balancing for shared flow

The aim of the second research question was to investigate the potential impact of positive and negative balancing on the experience of shared flow compared to no balancing. To address this, data from six pairs with a difference in fitness level were utilized. The results of the analysis revealed that there was no significant relationship observed between balancing and both the intensity of shared flow and percentage of time spent in shared flow. Additionally, autotelic personality did not exhibit a significant relationship with shared flow. The findings for the intensity of shared flow are presented in Table VIII and percentage of time spent in shared flow in Table IX. The random effect pair accounted for minimal variance, approximately 9% for the intensity of shared flow and 11% for percentage of time spent in shared flow, indicating that a considerable amount of variation in the model remained unexplained.

An additional analysis was conducted to investigate the potential influence of balancing on position, mean change in cadence, and mean sum of zeros in cadence, which were identified as potential proxies for shared flow in the first research question. Three figures were created to display the distribution of these variables across the three balancing conditions. As seen in Figure 11, pairs spent less time cycling next to each other during positive balancing compared to negative and no balancing. In negative balancing, as shown in Figure 12, pairs had more continuous cadence compared to positive and no balancing. Finally, Figure 13 demonstrates that pairs experienced more interruptions in cadence during positive balancing compared to negative and no balancing.

Table VI: The fixed effects structure of the mixed-effects logistic regression model for identifying proxies for shared flow

Fixed effects	Estimate (log odds)	SE	Z	P-value	95% CI Lower	95% CI Upper
Intercept	-1.21	0.55	-2.20	0.028	-2.76	0.43
Position	1.63	0.28	5.87	<0.001	1.10	2.19
Mean change in cadence	0.78	0.25	3.09	0.002	0.29	1.28
Mean sum of zeros in cadence	0.53	0.25	2.10	0.036	0.03	1.02
Autotelic personality score	0.43	0.18	2.34	0.019	-0.03	0.89

Table VII: The random effects structure of the mixed-effects logistic regression model for identifying proxies for shared flow

Random effects	Variance	SE
Pair	0.11	0.33
Balancing type	0.21	0.46
Difference in fitness level	0.33	0.57

Table VIII: The fixed effects structure of the mixed-effects linear regression model for exploring the effect of balancing on the intensity of shared flow

Fixed effects	Estimate	SE	T-value	P-value
Intercept	4.55	0.16	27.77	<0.001
Positive balancing	-0.13	0.22	-0.59	0.571
Negative balancing	-0.28	0.22	-1.28	0.231
Autotelic personality score	-0.04	0.10	-0.41	0.700

Table IX: The fixed effects structure of the mixed-effects linear regression model for exploring the effect of balancing on the percentage of time spent in shared flow

Fixed effects	Estimate	SE	T-value	P-value
Intercept	70.50	7.25	9.73	<0.001
Positive balancing	-13.00	9.73	-1.34	0.211
Negative balancing	-5.83	9.73	-0.60	0.562
Autotelic personality score	5.86	4.71	1.24	0.282

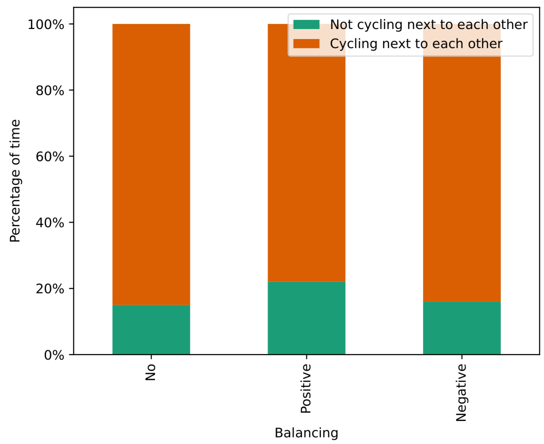


Figure 11: The percentage of time that pairs spent cycling next to each other and not in each of the balancing conditions

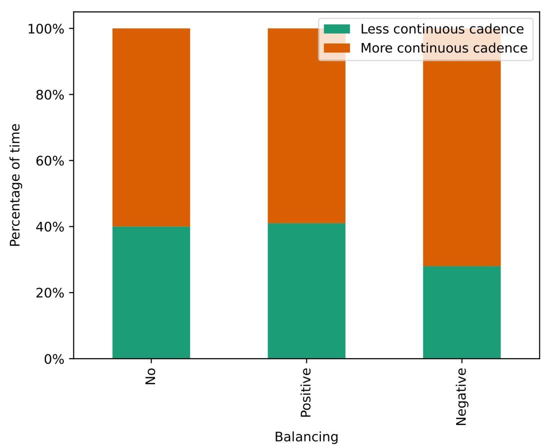


Figure 12: The percentage of time that pairs had less and more continuity in their cadence in each of the balancing conditions

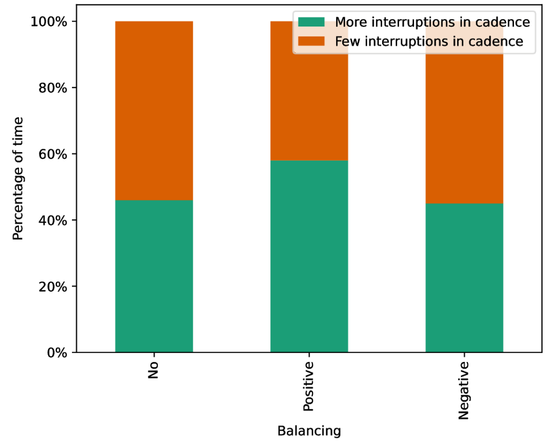


Figure 13: The percentage of time pairs spent cycling with more and fewer interruptions in cadence in each of the balancing conditions

V. Discussion

This discussion aims to provide insights into shared flow during cycling by analyzing the outcomes of the study. The discussion is structured into various sections. Firstly, the results of the correlational analysis aimed at identifying potential proxies for shared flow are examined. Secondly, the results from the investigation of the impact of positive and negative balancing on shared flow are discussed. Additionally, the discussion delves into definitional and operational issues related to shared flow, and methodological challenges encountered during the study. Throughout the discussion, recommendations for future research are provided to address these issues. Finally, the discussion highlights some interesting leads for future research.

A. *Proxies for shared flow*

The hypothesis that position, heart rate features, cadence features, or a combination of these could be used as indicators of shared flow experience on electric bicycles was partially confirmed. The results showed a significant correlation between shared flow and position as well as two cadence features, supporting the hypothesis. The contribution of heart rate features to the prediction of shared flow was not significant, leading to the rejection of the hypothesis regarding the relationship between heart rate features and shared flow. While this study found significant relationships between position and cadence features with shared flow experience, it should be noted that these relationships may not hold true in other contexts or with different populations. Additionally, the lack of a significant relationship between heart rate features and shared flow experience should not be interpreted as conclusive evidence, as different data collection or analysis methods may yield different results. Therefore, further research is needed to confirm and expand on these findings.

The mixed-effects logistic regression analysis revealed that position had a statistically significant association with shared flow (p-value$<$0.001). When participants cycled next to each other they had a 5.10 times greater likelihood of experiencing shared flow compared to when they were not cycling next to each other. This finding was consistent with the study's hypothesis. However, it is important to acknowledge that participants were aware of their position relative to each other while completing the flow timeline, and their interpretation of flow may have been influenced by this awareness. Nonetheless, the results suggest that position could serve as a suitable proxy for measuring flow.

The results of this study showed no significant relationship between heart rate and shared flow, either alone or in combination with position. This was contrary to the this study's hypothesis. There could be several explanations for this finding. Firstly, heart rate is affected by numerous factors such as physical fitness, age, gender, and mental stress (Valentini and Parati, 2009), which may have concealed any connection with shared flow. Secondly, the variance in heart rate in a thirty second interval may not be an appropriate measure of distractions or stress. Thirdly, the heart rate might react slower to changes, and its change may not have been captured within the same thirty-second interval. Lastly, it is possible that the participants were not adequately challenged for heart rate to respond due to the motor support of the electric bicycles. According to the results of this study, heart rate was not found to be a reliable indicator of shared flow. Nonetheless, it is important to note that this does not necessarily mean that heart rate cannot be used as a proxy for shared flow in other research, using different data collection or analysis methods. Additionally, it is possible that other heart rate features not explored in this study may have a stronger correlation with shared flow. Further research is needed to confirm these findings.

The analysis demonstrated that the cadence features of mean change and mean sum of zeros in cadence were significantly associated with shared flow (respectively, p-value = 0.002 and p-value = 0.036). A more continuous cycling cadence over time and less interruptions in cadence were both found to have a positive correlation with shared flow, albeit with respectively a moderate (OR = 2.18) and small (OR = 1.69) effect size. These findings were consistent with the initial hypotheses. The results of the interviews with participants supported these findings, as some of them reported cycling with an inconsistent cadence when they were distracted or cycling at a different pace than their partner.

The autotelic personality score also had a significant (p-value = 0.019) positive correlation (OR = 1.53) with shared flow. This was expected, as the people who are more prone to experience flow in their daily life, will also be more likely to experience shared flow in this experiment. Besides this finding, the inclusion of the autotelic personality score as a fixed effect also lowered the explained variance of the random effect pair.

The mixed-effects logistic regression analysis revealed that the variation in the data was predominantly explained by the difference in fitness level among the three random effects, followed by balancing type and pair. These findings were in line with the expectation that a difference in fitness level would have a significant impact on the shared cycling experience.

B. Balancing for shared flow

The study hypothesized that positive and negative balancing would increase the intensity of shared flow and percentage of time spent in shared flow for pairs with varying fitness levels compared to no balancing. A mixed-effects linear regression was conducted to assess the effects of balancing on shared flow. However, no significant relationship between balancing and shared flow was revealed. Neither did the results reveal a significant relationship between the autotelic personality score and shared flow, which was unexpected. This unexpected finding may be attributed to an inability of the adapted shared flow scale to measure shared flow and/or unmeasured factors influencing shared flow. The low variance explained by random effects suggests that other factors not included in the analysis were impacting shared flow.

Despite having differing levels of fitness, most pairs were already accustomed to each other and were used to not having an ideal challenge for their abilities. Therefore, the introduction of balancing may have disturbed the equilibrium among pairs who had previous cycling experience together, which was not taken into account during participant selection and may have contributed to the non-significant results. Secondly, the method of balancing, which involved adjusting the motor control system, may not have been appropriate. The difference in motor support between the two participants in the balancing conditions could have been too significant for their difference in fitness level. Some pairs that had different levels of fitness even preferred not to have balancing, as it created too big of a difference in their speed, which they did not like. In fact, in one pair, the fitter participant even mentioned having difficulty keeping up with the less-fit participant when balancing was applied. Furthermore, there may be other factors that impact shared flow, such as environmental conditions or individual characteristics of the participants, that were not taken into account in this study. Although balancing had no significant impact in this study, its potential cannot and should not be discounted. Further exploration is necessary to evaluate the effectiveness of balancing for different types of groups, such as heterogeneous groups with significant disparities in fitness levels.

The study also investigated the impact of balancing on the potential indicators of shared flow identified in the analysis of the first research question. The results suggested that positive balancing may have a negative effect on shared flow, as pairs cycled less often next to each other and experienced more interruptions in cadence. In contrast, negative balancing led to a more continuous cadence, which may be advantageous for the shared flow experience. However, these conclusions should be approached with care, as they rely on the assumption that the potential indicators accurately reflect shared flow. Additionally, the results cannot be generalized to other populations or contexts, as they may be highly specific to the target group and setting of the study.

C. Definitional and operational issues

This study has some potential limitations to consider regarding the definition and measurement of shared flow. One of these limitations is the possibility of varying interpretations of what constitutes a state of flow during cycling, despite participants being given the same definition. It is possible that participants interpreted flow as a positive cycling experience rather than shared flow, given that they experienced shared flow around 70% of the time. However, the fact that the participants were, on average, predisposed to experiencing shared flow (3.78 on the autotelic personality scale from 1 to 5) and that the study conditions allowed for it to occur suggests that shared flow was likely still measured. Another limitation of this study is its definition of shared flow, which only accounts for the time when both participants are in individual flow, disregarding the social elements that might be involved. Furthermore, the operationalization of shared flow may also have some limitations. While video-supported recall was utilized, it can still be challenging for participants to recall the exact moment when flow was experienced, especially in short thirty seconds intervals. Moreover, participants' memories may be influenced by visual cues, ignoring the impact of other factors on their cycling experiences. These limitations emphasize the importance of careful consideration and precision in designing and conducting research studies, especially when dealing with complex concepts like shared flow during cycling.

D. Methodological issues

Throughout the research process, several methodological challenges arose that had the potential to impact the accuracy and validity of the results. These challenges were categorized into three domains: study design, data collection methods, and data analysis. This section will address each of these domains in turn and will provide suggestions for addressing the limitations of each method to enable future researchers to conduct more reliable studies.

1) Study design: Regarding study design, the selection of participants was a concern as only pairs who were already accustomed to cycling with each other were invited to participate. This limited the positive impact of balancing, and future research should consider including participants with more obvious differences in fitness levels or those who have not cycled together before. Additionally, some participants were more familiar with the route than others, leading to different levels of preoccupation with locating the correct route, which affected their flow. Future studies could explore the use of signs or exclusively recruit participants who are familiar with the area.

All cycling rounds analyzed were conducted on the same two bicycles with a motor control system based on cadence rather than the current industry standard based on torque. This made participants feel less in control and less comfortable than on their own electric bicycles. Future studies should use bicycles that are closer to the current industry standard.

Finally, the balancing method may have been inaccurately applied, potentially affecting the results related to the impact of balancing on shared flow. The motor level support differences might have been too significant in positive and negative balancing, causing less fit participants to go faster than fitter participants, resulting in an unequal experience instead of balanced. Additionally, some participants felt less in control when given level five motor support, which could have negatively impacted their cycling experience. To address these concerns, future studies utilizing electric bicycle motor control systems could involve participants with greater fitness level differences or use smaller differences in motor level support when applying balancing. Lastly, it is recommended to avoid using the highest level of motor support, particularly with older adult participants, as it may have a detrimental effect on their experience.

2) Data collection methods: In this section, the limitations and potential biases of the various data collection methods used in this study are discussed. The methods discussed include self-reported data, heart rate and cadence sensors, camera-based position analysis, and shared flow data collection. Firstly, the self-reported data on fitness levels. This method of determining whether there is a difference in fitness level is prone to bias and inaccuracy. Future research could consider using fitness tests or recruiting participants with more apparent fitness differences to enhance the precision of data.

Manually labeling the start and end times of each round may have resulted in the heart rate or cadence data being off by about fifteen seconds. While this is regarded acceptable with the thirty-second intervals in this study, researchers could prevent this issue by recording the Unix timestamp at the beginning and end of each round.

The use of a single bicycle camera to determine the participants' position had limitations that affected their cycling behavior. Participants were asked to cycle on the same side of each other, which may not have been their usual cycling pattern. This could have influenced their positioning during the rounds and affected their cycling experience. To address this issue, future researchers could use a 360-degree camera and multiple QR codes. However, camera-based position analysis has more limitations, such as QR codes being unrecognizable if the camera's view is distorted. To estimate the cyclists' position, researchers could use alternative methods such as infrared, lasers, ultrasound, and Bluetooth. Nevertheless, each of these methods has its limitations.

The Empatica E4 wristband used in this study was unable to measure the interbeat interval accurately during movement, and as a result, it was not considered as a feature of heart rate. Future researchers should employ a different sensor that is able to measure this feature, as prior research indicates that the interbeat interval has the potential to serve as a proxy for flow and shared flow (Tozman et al., 2015; Tyagi et al., 2016). To ensure more precise measurements, it is suggested that researchers use a chest band instead of a wristband.

During the study, issues arose in collecting cycling cadence data in some rounds. One of the sensors produced missing or unreliable data, which resulted in only around half of the data being used in the statistical analysis for shared flow proxies. To prevent similar issues in future studies, researchers could conduct visual analysis of the data after each experiment to identify problematic sensors. This will enable them to rectify the issue before it affects subsequent experiments.

There were also several notable issues with the collection of shared flow data in this study. As shown in Section IV-A, there was a considerable amount of variability in the time spent in shared flow, but very little in the intensity of shared flow. This suggests that the adapted Shared Flow Scale used in this study was not effective at capturing shared flow accurately. To improve the scale, future studies could consider adapting it more specifically to the cycling context by including questions related to cycling experience dimensions and alternating affirmative and negative questions to reduce respondent agreement bias. For now, researchers are advised to use alternative questionnaires to determine the intensity of shared flow. Another issue with the collection of shared flow data is that participants may have influenced each other while completing the shared flow timeline since they were sitting next to each other and reading their thoughts aloud. A more effective approach would be to provide tablets for each participant to review the recording and wear noise-canceling headphones to avoid distractions or influence from the other participant. However, this may be challenging for older adult participants who are less comfortable with technology.

3) Data analysis: The use of mixed effects models in this study was driven by their ability to account for both fixed and random effects, making them suitable for more accurate estimation of coefficients and standard errors. These models are also capable of handling unbalanced data and some missing values. The models have certain assumptions that need to be met for accurate results. These assumptions include homoscedasticity, normality of residuals, absence of influential data points, and most importantly, independence. The lack of independence between multiple measures from the same pair was addressed by adding pair as a random effect. However, there is another lack of independence in measures taken over time, which was not accounted for in this study. The temporal dependencies among multiple measures gathered from each pair within a cycling round were not considered. As each time interval is not independent from the preceding one, it cannot be treated as such. Incorporating these time dependencies into the analysis would require a more sophisticated mixed-effects model, such as an autoregressive-moving average model, that integrates a within-subject covariance structure to accommodate time dependencies. Future researchers should consider this in their analysis to improve the accuracy of their results.

E. Future research

For future research, it is recommended to design a more comprehensive experiment that addresses the limitations of this study. This involves enhancing data collection and analysis methods, focusing on a more diverse group with greater variability in abilities, and minimizing variations in flow interpretation among participants. To gain a deeper understanding of shared flow in cycling, physiological measures beyond heart rate, such as respiratory rate, muscle activity, and electrodermal activity, could be employed. Additionally, neurological measures like brainwave activity and eye movements could be incorporated. Investigating the influence of environmental factors, such as cycling infrastructure and surroundings, could further advance knowledge in this area. Furthermore, exploring the impact of user control over the balancing experience, which could foster a sense of agency and facilitate a personalized experience, may be a promising avenue for research.

VI. Conclusion

In this study, valuable insights have been gained into the complexities of measuring and inducing shared flow among recreational cycling older adults. The study has provided some initial evidence on potential proxies for shared flow and the effects of balancing on shared flow. However, the validity of the findings is limited, and further research is necessary to confirm and extend these findings. To advance this field of study, future research should refine the study design by improving data collection and analysis methods, testing with diverse target groups, and incorporating additional physiological and neurological measures.

This study aimed to identify directly measurable proxies for shared flow and investigate the effect of positive and negative balancing on shared flow. The first research question aimed to determine whether position, heart rate, cadence, or a combination of these variables could serve as proxies for shared flow, and which features of these variables have a significant relationship with shared flow. The results showed that only position and mean change and sum of zeros in cadence were related to shared flow, indicating that these could function as measurable proxies for shared flow, but not heart rate. However, it is important to note that these significant relationships may not hold true in other contexts or with different populations. It is also important to note that the absence of a significant relationship between the heart rate features examined and shared flow should not be considered conclusive evidence. Varying data collection and analysis methods could potentially produce different results, and other heart rate features, such as the interbeat interval, should also be tested. Thus, further research is warranted to confirm and extend these findings.

The second research question aimed to examine the effect of positive and negative balancing on the intensity of shared flow and the percentage of time spent in shared flow, compared to no balancing. The results did not show a significant relationship, contrary to the initial hypothesis. An additional analysis was conducted to determine the effect of balancing on the potential proxies for shared flow, and the results suggested that negative balancing could be more suitable for inducing shared flow than positive balancing. However, this conclusion may be biased, and further testing is needed with different methods and in different contexts. A definitive conclusion about the impact of balancing on shared flow cannot be drawn yet.

VII. Acknowledgments

I would like to express my gratitude to everyone who supported me throughout my thesis writing journey. Firstly, I am thankful to my parents and sister for their unwavering belief in me. Next, a big thanks to my boyfriend for always being my supportive sounding board. I am also appreciative of the constructive feedback and guidance from Paul Havinga, and the critical observations and thought-provoking questions from Dees Postma. I am particularly grateful to my daily supervisor, Mario Boot, for his warm welcome, numerous brainstorming sessions, and our collaborative learning process. Finally, I extend my thanks to my colleagues at the Pervasive Systems Group, especially ”het fiets kamertje,” for their attentive listening and insightful inquiries.

REFERENCES

Abbiss, C., Peiffer, J. and Laursen, P. (2009), 'Optimal cadence selection during cycling', *International SportMed Journal* **10**(1).

Altimira, D., Mueller, F. F., Clarke, J., Lee, G., Billinghurst, M. and Bartneck, C. (2016), Digitally augmenting sports: An opportunity for exploring and understanding novel balancing techniques, *in* 'Conference on Human Factors in Computing Systems - Proceedings', Association for Computing Machinery, San Jose, CA, USA, pp. 1681–1691.

Altimira, D., Mueller, F. F., Lee, G., Clarke, J. and Billinghurst, M. (2014), Towards understanding balancing in exertion games, *in* 'ACM International Conference Proceeding Series', Vol. 2014-November, Association for Computing Machinery, Funchal, Portugal.

Bateman, S., Mandryk, R. L., Stach, T. and Gutwin, C. (2011), Target assistance for subtly balancing competitive play, *in* 'Conference on Human Factors in Computing Systems - Proceedings', Vancouver, Canada, pp. 2355–2364.

Bates, D., Mächler, M., Bolker, B. and Walker, S. (2015), 'Fitting Linear Mixed-Effects Models Using lme4', *Journal of Statistical Software* **67**(1).

Bayrak, A. T., Kumar, R., Tan, J., AhMu, D., Hohepa, J., Shaw, L. A., Lutteroth, C. and Wünsche, B. C. (2017), Balancing different fitness levels in competitive exergames based on heart rate and performance, *in* 'ACM International Conference Proceeding Series', Association for Computing Machinery, Brisbane, Australia, pp. 210–217.

Bent, B., Goldstein, B. A., Kibbe, W. A. and Dunn, J. P. (2020), 'Investigating sources of inaccuracy in wearable optical heart rate sensors', *npj Digital Medicine* **3**(1).

Bradski, G. (2000), 'The OpenCV Library', *Dr. Dobb's Journal of Software Tools* .

CBS Statistics Netherlands (2022), 'Elderly people'.
URL: *https://www.cbs.nl/en-gb/visualisations/dashboard-population/age/elderly-people (accessed on 13-04-2023)*

Cechanowicz, J., Gutwin, C., Bateman, S., Mandryk, R. L. and Stavness, I. (2014), Improving player balancing in racing games, *in* 'CHI PLAY 2014 - Proceedings of the 2014 Annual Symposium on Computer-Human Interaction in Play', Association for Computing Machinery, Toronto, ON, Canada, pp. 47–56.

Csikszentmihalyi, M. (1975), *Beyond boredom and anxiety*, 1 edn, Jossey-Bass Publishers, San Fransisco.

Csikszentmihalyi, M. (2014), *Flow and the Foundations of Positive Psychology: The collected works of Mihaly Csikszentmihalyi*, Springer, Dordrecht.

Csikszentmihalyi, M., Abuhamdeh, S. and Nakamura, J. (2005), Flow, *in* E. Elliot and C. Dweck, eds, 'Handbook of competence and motivation', The Guilford Press, New York, pp. 598–608.

Elbe, A.-M., Barene, S., Strahler, K., Krustrup, P. and Holtermann, A. (2016), 'Experiencing Flow in a Workplace Physical Activity Intervention for Female Health Care Workers: A Longitudinal Comparison between Football and Zumba', *Women in Sport and Physical Activity Journal* **24**(1), 70–77.

Fong, C. J., Zaleski, D. J. and Leach, J. K. (2015), 'The challenge–skill balance and antecedents of flow: A meta-analytic investigation', *Journal of Positive Psychology* **10**(5), 425–446.

García Calvo, T., Jiménez Castuera, R., Santos-Rosa Ruano, F. J., Reina Vaíllo, R. and Cervelló Gimeno, E. (2008), 'Psychometric properties of the spanish version of the flow state scale', *Spanish Journal of Psychology* **11**(2), 660–669.

Gerling, K. M., Miller, M., Mandryk, R. L., Birk, M. and Smeddinck, J. (2014), Effects of skill balancing for physical abilities on player performance, experience and self-esteemin exergames, *in* 'Conference on Human Factors in Computing Systems - Proceedings', Association for Computing Machinery, Toronto, ON, Canada, pp. 2201–2210.

Goddard, S. G., Stevens, C. J., Jackman, P. C. and Swann, C. (2021), 'A systematic review of flow interventions in sport and exercise', *International Review of Sport and Exercise Psychology* .

Hart, E. and Di Blasi, Z. (2015), 'Combined flow in musical jam sessions: A pilot qualitative study', *Psychology of Music* **43**(2), 275–290.

Heinen, E., van Wee, B. and Maat, K. (2010), 'Commuting by bicycle: An overview of the literature', *Transport Reviews* **30**(1), 59–96.

Jackman, P. C., Hawkins, R. M., Crust, L. and Swann, C. (2019), 'Flow states in exercise: A systematic review', *Psychology of Sport and Exercise* **45**.

Jackson, S. A. and Marsh, H. W. (1996), 'Development and Validation of a Scale to Measure Optimal Experience: The Flow State Scale', *Jounral of Sport & Exercise Physiology* **18**, 17–35.

Katahira, K., Yamazaki, Y., Yamaoka, C., Ozaki, H., Nakagawa, S. and Nagata, N. (2018), 'EEG correlates of the flow state: A combination of increased frontal theta and moderate frontocentral alpha rhythm in the mental arithmetic task', *Frontiers in Psychology* **9**.

Khoo, E. T., Cheok, A. D., Nguyen, T. H. D. and Pan, Z. (2008), 'Age invaders: Social and physical inter-generational mixed reality family entertainment', *Virtual Reality* **12**(1), 3–16.

Kiili, K. and Perttula, A. (2010), Exergaming: Exploring engagement principles, *in* J. Wiemeyer and S. Göbel, eds, 'Serious

Games for Sports and Health, Proceedings-Game Days', Darmstadt, Germany, pp. 161–172.

Klasen, M., Weber, R., Kircher, T. T., Mathiak, K. A. and Mathiak, K. (2012), 'Neural contributions to flow experience during video game playing', *Social Cognitive and Affective Neuroscience* **7**(4), 485–495.

Kraaijenbrink, E., van Gils, F., Cheng, Q., van Herk, R. and van den Hoven, E. (2009), Balancing Skills to Optimize Fun in Interactive Board Games, *in* 'Human-Computer Interaction – INTERACT', pp. 301–313.

Krizek, K. J., Johnson, P. J. and Tilahun, N. (2005), 'Gender Differences in Bicycling Behavior and Facility Preferences', *Research on Women's Issues in Transportation* **2**, 31–40.

Kruschewsky, A. B., Dellagrana, R. A., Rossato, M., Ribeiro, L. F. P., Lazzari, C. D. and Diefenthaeler, F. (2018), 'Saddle Height and Cadence Effects on the Physiological, Perceptual, and Affective Responses of Recreational Cyclists', *Perceptual and Motor Skills* **125**(5), 923–938.

Lee, C. and Payne, L. L. (2016), 'Experiencing flow in different types of serious leisure in later life', *World Leisure Journal* **58**(3), 163–178.

Liu, G., Krishnamurthy, S. and van Wesemael, P. (2021), 'Conceptualizing cycling experience in urban design research: a systematic literature review', *Applied Mobilities* **6**(1), 92–108.

Lucía, A., Hoyos, J. and Chicharro, J. L. (2001), 'Preferred pedaling cadence in professional cycling', *Medicine and science in sports and exercise* **33**(8), 1361–1366.

Łucznik, K. and May, J. (2021), 'Measuring individual and group flow in collaborative improvisational dance', *Thinking Skills and Creativity* **40**(5).

MacDonald, R., Byrne, C. and Carlton, L. (2006), 'Creativity and flow in musical composition: an empirical investigation', *Psychology of Music* **34**(3), 292–306.

McKinney, W. (2010), Data Structures for Statistical Computing in Python, *in* S. Van der Walt and J. Millman, eds, 'Proceedings of the 9th Python in Science Conference', pp. 56–61.

Muangsrinoon, S. and Boonbrahm, P. (2017), Burn in Zone: Real time Heart Rate monitoring for physical activity, *in* '2017 14th International Joint Conference on Computer Science and Software Engineering', IEEE, pp. 1–6.

Mueller, F. F., Vetere, F., Gibbs, M. R., Edge, D., Agamanolis, S., Sheridan, J. G. and Heer, J. (2012), Balancing exertion experiences, *in* 'Proceedings of the SIGCHI Conference on Human Factors in Computing Systems', ACM, Austin, USA, pp. 1853–1862.

Nacke, L. E., Stellmach, S. and Lindley, C. A. (2011), 'Electroencephalographic assessment of player experience: A pilot study in affective ludology', *Simulation and Gaming* **42**(5), 632–655.

Nasri, A., Younes, H. and Zhang, L. (2020), 'Analysis of the effect of multi-level urban form on bikeshare demand: Evidence from seven large metropolitan areas in the United States', *Journal of Transport and Land Use* **13**(1), 389–408.

Natural History Museum (2021), 'PyZBar'.
URL: *https://github.com/NaturalHistoryMuseum/pyzbar (accessed on 13-04-2023)*

Nes, B. M., Janszky, I., Wisløff, U., Støylen, A. and Karlsen, T. (2013), 'Age-predicted maximal heart rate in healthy subjects: The HUNT Fitness Study', *Scandinavian Journal of Medicine and Science in Sports* **23**(6), 697–704.

Oliveira, W., Tenório, K., Hamari, J., Pastushenko, O. and Isotani, S. (2021), 'Predicting students' flow experience through behavior data in gamified educational systems', *Smart Learning Environments* **8**(1).

Park, J. H., Moon, J. H., Kim, H. J., Kong, M. H. and Oh, Y. H. (2020), 'Sedentary Lifestyle: Overview of Updated Evidence of Potential Health Risks', *Korean Journal of Family Medicine* **41**(6), 365–373.

Peifer, C., Wolters, G., Harmat, L., Heutte, J., Tan, J., Freire, T., Tavares, D., Fonte, C., Andersen, F. O., van den Hout, J., Šimleša, M., Pola, L., Ceja, L. and Triberti, S. (2022), 'A Scoping Review of Flow Research', *Frontiers in Psychology* **13**.

Pels, F., Kleinert, J. and Mennigen, F. (2018), 'Group flow: A scoping review of definitions, theoretical approaches, measures and findings', *PLoS ONE* **13**(12).

Pelzer, P. (2012), 'Nieuwe perspectieven op fietscultuur', *Tijdschrift Vervoerswetenschap* **48**(4).

Petosa, R. L. and Holtz, B. (2013), 'Flow for Exercise Adherence: Testing an Intrinsic Model of Health Behavior', *American Journal of Health Education* **44**(5), 273–277.

Popan, C. (2020), 'Beyond utilitarian mobilities: cycling senses and the subversion of the car system', *Applied Mobilities* **5**(3), 289–305.

Pucher, J. (2012), *City Cycling*, The MIT Press.

R Core Team (2022), 'R: A Language and Environment for Statistical Computing'.
URL: *https://www.R-project.org/ (accessed on 13-04-2023)*

Rijksoverheid (n.d.), 'CycleOn: bike safety and vitality for elderly'.
URL: *https://www.government.nl/topics/bicycles/cycleon-bike-safety-and-vitality-for-elderly (accessed on 13-04-2023)*

Salanova, M., Rodríguez-Sánchez, A. M., Schaufeli, W. B. and Cifre, E. (2014), 'Flowing together: a longitudinal study of collective efficacy and collective flow among workgroups.', *The Journal of psychology* **148**(4), 435–455.

Sawyer, R. K. (2003), *Group Creativity: Music, theater, collaboration*, 1 edn, Psychology Press.

Schüler, J. and Brunner, S. (2009), 'The rewarding effect of flow experience on performance in a marathon race', *Psychology of Sport and Exercise* **10**(1), 168–174.

Singh Thakur, T. and Madhusudhana Babu, P. (2019), 'Evolution of Bicycles and their utility as Fitness aids - A Review', *Journal of Nursing and Health Science* **8**(3), 19–23.
URL: *https://www.researchgate.net/publication/333131892 (accessed on 13-04-2023)*

Singleton, P. A. (2019), 'Walking (and cycling) to well-being: Modal and other determinants of subjective well-being during the commute', *Travel Behaviour and Society* **16**, 249–261.

Sonne, T. and Jensen, M. M. (2014), Race By Hearts: Using Technology to Facilitate Enjoyable and Social Workouts, *in* 'Entertainment Computing – ICEC 2014', Sydney, Australia.

Spinney, J. (2009), 'Cycling the city: Movement, meaning and method', *Geography Compass* **3**(2), 817–835.

Stach, T. B. (2012), Heart Rate Balancing for Multiplayer Exergames, PhD thesis, Queen's University, Kingston, Canada.

Stach, T. and Graham, T. C. (2011), Exploring haptic feedback in exergames, *in* 'Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)', Vol. 6947 LNCS, Lisbon, Portugal, pp. 18–35.

Swann, C., Driscoll, J., Goddard, S. G., Willis, R., Schweickle, M. J., Fernandes Ribeiro, I. A., Gatt, M., Jackman, P. C. and Vella, S. A. (2022), 'The Flow-Clutch Scale: Development and preliminary validation in sport and exercise', *Psychology of Sport and Exercise* **58**.

Swann, C. F., Keegan, R. J., Piggott, D., Crust, L., Swann, C. and Keegan, R. J. (2012), 'A systematic review of the experience, occurrence, and controllability of flow states in elite sport', *Psychology of Sport and Exercise* **13**, 807–819.

Thin, A. G., Hansen, L. and McEachen, D. (2011), 'Flow experience and mood states while playing body movement-controlled video games', *Games and Culture* **6**(5), 414–428.

Tian, Y., Bian, Y., Han, P., Wang, P., Gao, F. and Chen, Y. (2017), 'Physiological signal analysis for evaluating flow during playing of computer games of varying difficulty', *Frontiers in Psychology* **8**.

Tozman, T., Magdas, E. S., MacDougall, H. G. and Vollmeyer, R. (2015), 'Understanding the psychophysiology of flow: A driving simulator experiment to investigate the relationship between flow and heart rate variability', *Computers in Human Behavior* **52**, 408–418.

Tse, D. C., Lau, V. W. y., Perlman, R. and McLaughlin, M. (2020), 'The Development and Validation of the Autotelic Personality Questionnaire', *Journal of Personality Assessment* **102**(1), 88–101.

Tyagi, A., Cohen, M., Reece, J., Telles, S. and Jones, L. (2016), 'Heart Rate Variability, Flow, Mood and Mental Stress During Yoga Practices in Yoga Practitioners, Non-yoga Practitioners and People with Metabolic Syndrome', *Applied Psychophysiology Biofeedback* **41**(4), 381–393.

Valentini, M. and Parati, G. (2009), 'Variables Influencing Heart Rate', *Progress in Cardiovascular Diseases* **52**(1), 11–19.

Van Deemter, S., Wendel-Vos, W. and De Hollander, E. (2022), 'Elektrisch fietsen in Nederland'.
URL: *https://www.rivm.nl/publicaties/elektrisch-fietsen-in-nederland (accessed on 04-04-2023)*

Van Hagen, M. and Govers, B. (2019), Durven, kunnen en willen fietsen - de klantwensenpyramide voor reizigers toegepast op fietsbeleid.

Van Rossum, G. and Drake, F. L. (2009), *Python 3 Reference Manual*, CreateSpace, Scotts Valley, USA.

Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S. J., Brett, M., Wilson, J., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., Carey, C. J., Polat, I., Feng, Y., Moore, E. W., VanderPlas, J., Laxalde, D., Perktold, J., Cimrman, R., Henriksen, I., Quintero, E. A., Harris, C. R., Archibald, A. M., Ribeiro, A. H., Pedregosa, F., van Mulbregt, P., Vijaykumar, A., Bardelli, A. P., Rothberg, A., Hilboll, A., Kloeckner, A., Scopatz, A., Lee, A., Rokem, A., Woods, C. N., Fulton, C., Masson, C., Häggström, C., Fitzgerald, C., Nicholson, D. A., Hagen, D. R., Pasechnik, D. V., Olivetti, E., Martin, E., Wieser, E., Silva, F., Lenders, F., Wilhelm, F., Young, G., Price, G. A., Ingold, G.-L., Allen, G. E., Lee, G. R., Audren, H., Probst, I., Dietrich, J. P., Silterra, J., Webber, J. T., Slavič, J., Nothman, J., Buchner, J., Kulick, J., Schönberger, J. L., de Miranda Cardoso, J. V., Reimer, J., Harrington, J., Rodríguez, J. L. C., Nunez-Iglesias, J., Kuczynski, J., Tritz, K., Thoma, M., Newville, M., Kümmerer, M., Bolingbroke, M., Tartre, M., Pak, M., Smith, N. J., Nowaczyk, N., Shebanov, N., Pavlyk, O., Brodtkorb, P. A., Lee, P., McGibbon, R. T., Feldbauer, R., Lewis, S., Tygier, S., Sievert, S., Vigna, S., Peterson, S., More, S., Pudlik, T., Oshima, T., Pingel, T. J., Robitaille, T. P., Spura, T., Jones, T. R., Cera, T., Leslie, T., Zito, T., Krauss, T., Upadhyay, U., Halchenko, Y. O. and Vázquez-Baeza, Y. (2020), 'SciPy 1.0: fundamental algorithms for scientific computing in Python', *Nature Methods* **17**(3), 261–272.

Walker, C. J. (2010), 'Experiencing Flow: Is Doing It Together Better Than Doing It Alone?', *The Journal of Positive Psychology* **5**(1).

Wang, C.-C. and Hsu, M. (2013), Flow Experience and Challenge-Skill Balance in E-Learning, *in* 'PACIS 2013 Proceedings', Jeju Island, Korea, p. 203.

Wang, C. C. and Hsu, M. C. (2014), 'An exploratory study using inexpensive electroencephalography (EEG) to understand

flow experience in computer\-based instruction', *Information and Management* **51**(7), 912–923.
Waskom, M. (2021), 'Seaborn: statistical data visualization', *Journal of Open Source Software* **6**(60), 3021.
Zumeta, L., Wlodarczyk, A., Basabe, N., Telletxea, S., Alves, D. and Puente, A. (2013), Shared flow and emotional communion in collective activities, *in* 'Poster on 12th ECPA', Donostia/San Sebastián, Spain.

Appendix A: The adapted Shared Flow Scale

This Appendix contains the adapted Shared Flow Scale used in the study.

Table A-1: The adapted Shared Flow Scale

Dimension of flow	**Item**
(1) Challenge-skill balance	Our fitness and skill levels matched the challenges we faced
(2) Merging of action and awareness	We felt everything went automatically
(3) Clear goals	We knew clearly what to do
(4) Unambiguous feedback	It was clear to us we were doing well
(5) Concentration on the task at hand	We were concentrated on what we were doing
(6) Sense of control	We felt in control over what we were doing
(7) Loss of self-consciousness	We did not worry about what others might think of us
(8) Transformation of time	We felt that time passed differently than normally
(9) Autotelic experience	We really enjoyed what we were doing

Appendix B

This Appendix presents the formulas used for feature extraction that were developed by the researchers and not obtained from any pre-existing library in Python. In the formulas, $p(1)$ and $p(2)$ represent participant 1 and participant 2, respectively, and $t(x)$ and $t(x-1)$ indicate the current and previous thirty-second interval. Formula 1 was used to calculate the mean change in heart rate. Similarly, the mean change in cadence was calculated. Formulas 2, 3, and 4 were used to determine the similarity in heart rate exertion.

$$HR_{meanchange_{t(x)}} = \frac{\begin{array}{c}|HR_{mean_{p(1)t(x)}} - HR_{mean_{p(1)t(x-1)}}| \\ + |HR_{mean_{p(2)t(x)}} - HR_{mean_{p(2)t(x-1)}}|\end{array}}{2} \tag{1}$$

$$HR_{relative_{t(x)}} = \frac{HR_{mean_{t(x)}}}{HR_{max}} \tag{2}$$

$$HR_{max} = \frac{HR}{211 - 0.64 * age} \tag{3}$$

$$HR_{similarity_{t(x)}} = \frac{HR_{relative_{p(1)t(x)}}}{HR_{relative_{p(2)t(x)}}} \tag{4}$$