Interacting with Computers, 2024, 1–15
https://doi.org/10.1093/iwc/iwae012
Article

From Metrics to Experiences: Investigating How Sport Data Shapes the Social Context, Self-Determination and Motivation of Athletes

Dees Postma[1], Dennis Reidsma[1], Robby van Delden[1] and Armağan Karahanoğlu[2,*]

[1]Faculty of Electrical Engineering and Mathematics and Computer Science, Department of Human Media Interaction, University of Twente Enschede, Enschede, the Netherlands
[2]Faculty of Engineering Technology, Interaction Design Research Group, University of Twente, Enschede, the Netherlands
Corresponding author: a.karahanoglu@utwente.nl

In this paper, we use self-determination theory and its related mini-theories to investigate the influence of sport data on sports experience and motivation in sports. First, we reflect on the use of technology in sports and show how sport data thwarts and promotes motivation in sports. Second, we argue that human–computer interaction (HCI) has been too narrowly focused on the 'performance' aspect of sport data. We argue for a more liberal take on sport data, showing that it also relates to motivation in sports through basic human needs. By bridging SportsHCI studies with the insights we gain from self-determination theory, we uncover the interwoven relations between the objective measures that sports technology provides and their motivational aspects for athletes. Our paper ends with five emerging points for attention for SportsHCI that we think can pave the way towards a more holistic approach to considering sport data for motivation in sports.

RESEARCH HIGHLIGHTS

- We demonstrate the value of Self-Determination Theory (SDT) and its sub-theories by critically analysing how sport data shapes sporting experience.
- We explore the impact of sport data on athletes' physical, social, intellectual, and emotional well-being through the lens of SDT.
- We explain how SDT accounts for the use of sport data in athlete flourishing, intrinsic motivation, sport motivation regulation and sport goals and aspirations.
- We introduce an initial definition of "Sport-Data Experience (SDX)" based on SDT and propose research directions for unpacking the dimensions of SDX.

Keywords: *Self Determination Theory; SportsHCI; Sport data experience; Sports Interaction Technology*

1. INTRODUCTION

Sport data plays an increasingly important role in the training practices of (amateur) athletes. Apps, sports watches and activity trackers are the most frequently used sports technologies. For example, a recent report valued the global sports watches market at 25.6B in 2021, with a projected growth of 54.9B in 2030[1]. Similar trends are observed for the 'running apps market'[2], indicating an upsurge in interest in sport data for sport practice.

Researchers in human–computer interaction (HCI), data science and sports science have picked up on this trend by furthering the sensing capabilities of sport wearables, rendering sport data more accurate, reliable and valid in reflecting athletes' performance and efforts. Wearables no longer only provide users with distance and time measurements; machine learning and miniaturization have enabled such devices to also offer more in-depth metrics *on the fly* (e.g. ground-contact time) or *after* training (e.g. recovery time).

Beyond simply tracking, sports technology enables athletes to plan their training, pace their effort during training, and review their performance afterwards (Jowett et al., 2016; Postma et al., 2022). Sport data can even help athletes better understand their training load and recovery, providing in-depth insights into its underlying factors, like sleep quality (Karahanoğlu et al., 2021). While the focus of sports technologies is clearly on bettering the performance of the user, we have also witnessed other uses of sport data that drive motivation to play sports (e.g. social sharing). Athletes also report other uses: they use sports technology to compare themselves with others, which serves as a motivator for self-improvement (Kuru, 2016).

Several recent studies addressed the increased and influential role of data use in sporting experience (Menheere et al., 2020; Karahanoğlu et al., 2021; Restrepo et al., 2022). We argue

[1] https://www.alliedmarketresearch.com/sports-watches-market-A16907 last retrieved 9 February 2024.
[2] https://reports.valuates.com/market-reports/QYRE-Auto-13O2550/global-running-apps last retrieved 9 February 2024.

Received: July 28, 2023. **Revised:** February 14, 2024. **Accepted:** March 5, 2024

that although improving data accuracy becomes one of the driving forces of sports technology development (Rapp and Tirabeni, 2020), developing technology is not (just and only) about getting more accurate performance data. It is also about getting meaningful insights into supporting athletes' experiences regarding their goals, needs and motivations. As a result, from the experiential perspective, the sensemaking of the data (Coşkun and Karahanoğlu, 2023) and how the sensemaking feeds back into people's sports identity and how people engage with sports activity are essential inquiries yet under-addressed.

We argue that seeing sport data as a performance measure *only minimally* supports sports participation and autotelic experiences (Csikszentmihalyi, 1990). This view largely overlooks the experiential side of utilizing sport data. To tackle this limitation, we provide an overview of the experiential and motivational aspects of—and around—sport data. As such, there are different angles to how sport data can support experience and motivation in sports. This paper uses Self-Determination Theory to systematically unpack how sport data interacts with athletes' social context, self-determination, and motivation.

SDT has been used productively for sports science and HCI studies. For example, Jowett et al. (Jowett et al., 2016) found that satisfaction with Basic Psychological Needs fosters athlete's sports engagement and reduces the risks of burnout, while Turner et al. (Turner et al., 2022) provide evidence that high intrinsic motivation and athlete's self-belief work as the key parameters for physical and mental well-being. Rockmann (Rockmann, 2019) described SDT as fitting very well in the context of sports. However, most related work focuses on a performance-oriented perspective (i.e. understanding how performance feedback affects sports motivation [e.g. (Knaving et al., 2015; Kuru, 2016; Havlucu et al., 2019)]). Many of those studies that connect SDT to sports use mainly the Basic Psychological Needs Theory to define how to motivate people towards performance, adherence, training and learning, which we think also does not do full justice to the space of possibilities.

In light of these, to fully grasp the value of sport data for sports participation, we will explore the underlying sub-theories of SDT to illustrate how they can support the experience of and motivational aspects of sport data. Building upon this argument, we believe that SDT has the potential to connect sports science, sports psychology and HCI research in manifesting an agenda for SportsHCI research by creating awareness about the role of sport data in athletes' motivation. This understanding will lead to new interaction design possibilities with sport data that will address a broader range of values in sports. Therefore, we believe it is worth expanding the role of sport data in sports practice from the lens of SDT.

2. SPORT DATA: DEFINITION AND SCOPE

For some athletes, sport data has a functional role. It serves as immediate feedback that helps athletes improve their performance and skills (e.g. time or scores, as in Fig. 1-A) or prevent injuries (e.g. estimated post-training recovery time). However, sport data is predominantly intangible, and it only makes sense when analysed with and within the sports context (e.g. relative effort calculations, as in Fig. 1-B). We define sport data as *the data directly and only related to the athletes health, well-being (physiological, physical and mental) and sporting experience*. Therefore, any data collected for, about and within an athlete's sports performance is sport data (e.g. comparisons of prior sports activities Fig. 1-C and 1-D). Relatedly, data that an athlete collects with a smartwatch during sports (e.g. the heart rate data) is an integral part of understanding one's performance and is regarded as sport data, just as derived values (e.g. fitness change analysis, e.g. Fig. 1-E) and prediction metrics (e.g. race predictions) that sports technology provides. Although such metrics play a significant role in motivation, they are merely entry-level necessities.

Sport data is about how technology analyses and informs athletes about their sports activities and goals. In that sense, it encompasses any data that illustrates the quality of life of athletes (e.g. sleep score that shows the sleep quality or the athletes' adjusted daily water consumption, as in Fig. 1-F). Sport data is not always quantitative: we also consider qualitative values, such as the words 'hard' or 'easy' that illustrate the perceived exertion of an athlete, as sport data (e.g. Fig. 1-G, which shows the daily activities of an athlete as well as the 'maintaining' training status based on recent activities).

We should highlight that both individual and team sports can benefit from sport data. Data collected with wearables and sensors embedded in the environment is also within our definition of sport data. In some sports contexts, athletes' physiological data cannot be collected due to the rules and regulations of certain sports. For example, basketball players are generally not allowed to wear any technology during play, so athletes' HR data cannot be collected during basketball matches. Still, shot statistics (e.g. Home Court[3]) collected through computer vision or manual annotation and used to inform the athletes and potentially gameplay (Chatham and Mueller, 2013) is also sport data.

We focus on athlete-centric sport data, and therefore, we exclude big data from our definition of sport data when it only informs the gameplay or organizations. Any data that does not directly impact the way athletes experience sports (e.g. big data leveraged for drafting players) and does not inform the athletes about their health or sporting experience is beyond the scope of our definition. For example, the use of soccer data sonification for audience entertainment in a football match (Savery et al., 2019) has nothing to do with the experience, health and well-being of athletes. Therefore, such data is excluded from our definition of sport data.

Within these boundaries, sport data can be represented in numbers, words and graphics (Fig. 1). Athletes interact with the sport data through haptic cues, sounds and visuals that signal them about training performance and goals, which add value to and impact sports motivation.

3. RELATED WORK

3.1. A brief summary of motivation in sports psychology

Each athlete has unique training habits, aspirations and drives to participate in sports (Ogles and Masters, 2000; Vlachopoulos et al., 2000; Clancy et al., 2016). For example, young athletes often mention that learning a new skill or bettering existing skills is a driving factor to participate in sports [e.g. (Sit and Lindner, 2005; Kondric et al., 2013)]. Motivation in sports is a complex and multi-dimensional concept, with various interconnected theories explaining the reasons behind individuals' engagement, perseverance and performance in athletic activities (McCormick et al., 2019; Taylor et al., 2020). Below, we will summarize some of the most influential theories on motivation, which have ties to sports motivation. These theories, while distinct, collectively provide a holistic view of the motivational landscape in sports psychology.

[3] https://www.homecourt.ai last retrieve on 9 February 2024.

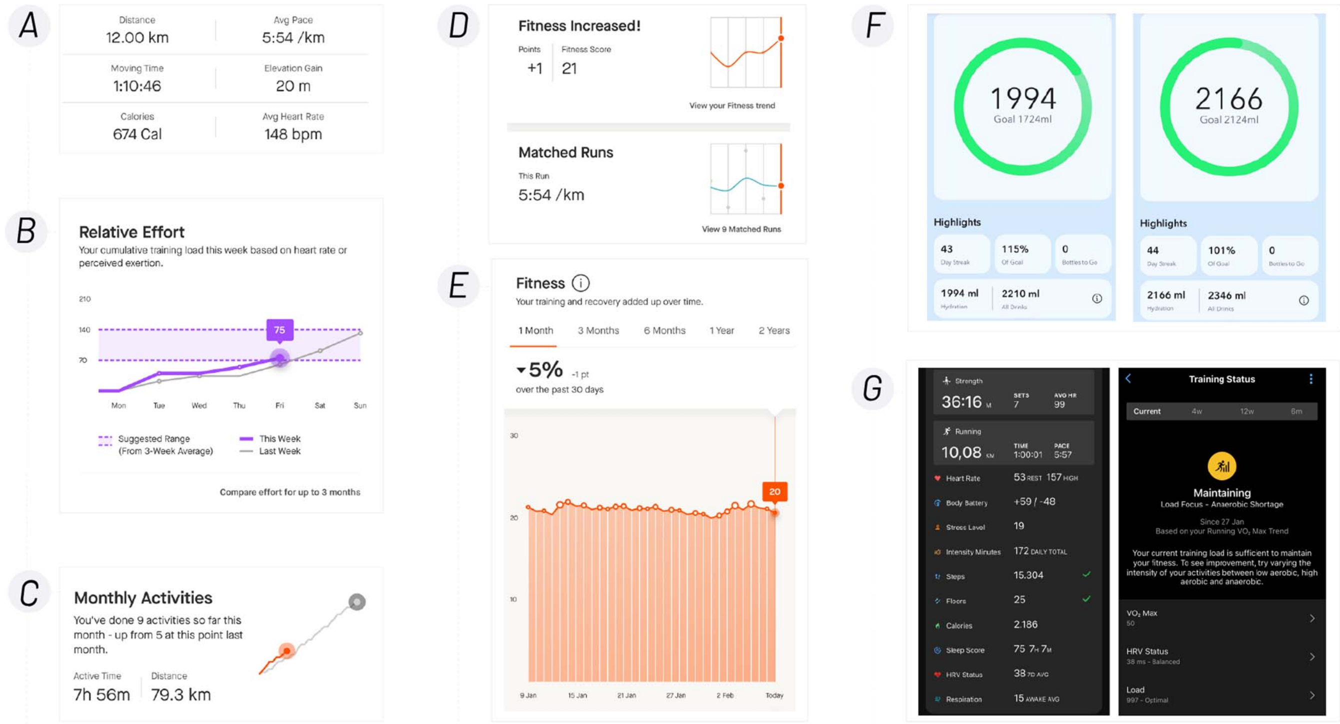

FIGURE 1. Examples of Sport Data. The images in A-E are from the Strava App; F is from Hidrate Spark, and G is from the Garmin Connected App[5]. (Copyright: Authors).

One of the significant strands of motivation research in sport psychology is Attribution Theory (Weiner, 1985; Weiner, 2012b), which concerns the processes by which people understand, interpret and explain their success and failure in everyday events: *It is contended that the interpretation of the past, that is, the perceived causes of prior events, determine what will be done in the future.* [(Weiner, 2012a), pg. 136]. Attribution Theory typically recognizes four determinants of behavioural outcome (i.e. ability, effort, task difficulty and luck) that can be organized along three causal dimensions (i.e. causal locus, causal stability and causal control). Accordingly, causal locus refers to whether an athlete perceives their success/failure to be attributable to internal factors (e.g. *I gave it my all*) or external factors (e.g. *my opponent was excellent today*). Causal stability refers to whether an athlete attributes their success or failure to stable factors (e.g. *I am very good at this*) or unstable factors (e.g. *I was lucky today*). Finally, causal control refers to whether attributions are controllable (e.g. *I had a good game plan*) or not (e.g. *the weather conditions were just terrible*). For our scope, Attribution Theory is important as it highlights the psychological aspect of motivation, showing how internal and external attributions can shape an athlete's motivational stance (Le Foll et al., 2008; McAuley and Duncan, 2014).

Need Achievement Theory (NAT) (McClelland, 2015) offers another approach to frame motivation, with clear parallels to Attribution Theory. NAT explains motivation as the interaction between personal attributes (i.e. pursuit of success and avoidance of failure) and situational factors (i.e. probability of success and incentive for success). Accordingly, individuals have a stronger tendency towards the avoidance of failure or towards the realization of success. If the hope of success is perceived to be greater than the fear of failure, people are likely to engage in a particular achievement-oriented activity. In line with these, athletes who are drawn towards success will likely seek out activities that match their skills. For them, winning against an equally skilled opponent feels more rewarding. Conversely, athletes who tend to avoid failure will experience a loss from a similarly skilled opponent more negatively and will likely seek out opponents from which they are either likely to win or likely to lose (Weinberg and Gould, 2023).

Achievement Goal Theory (AGT) provides further insights into motivation by organizing it into task-oriented and ego-oriented motivation (Nicholls, 1984; Dweck, 1986). Task-oriented motivation, or mastery-approach goals, emphasizes personal improvement, learning and skill development. In contrast, ego-oriented motivation, akin to performance-approach goals, focuses on outperforming others, aligning more closely with extrinsic motivation. For AGT, mastery-approach goals are typically linked to higher motivation, more adaptive behaviours and long-term success, suggesting a more sustainable form of motivation than ego-oriented goals (Duda, 1989; Senko et al., 2011; Harwood et al., 2015). Specifically, task-oriented athletes focus more on self-set success achievement criteria. In contrast, ego-involved athletes endorse external criteria (e.g. social approval) more as success criteria in sport experience (Lochbaum and Roberts, 1993).

While AGT distinguishes between goal orientations, Goal-Setting Theory (GST) highlights the effectiveness of setting specific, challenging, and attainable goals (Locke et al., 1981; Locke and Latham, 1990; Locke and Latham, 1994). The core concepts of GST align with task versus ego-oriented goals, as goals can be internally driven (e.g. personal growth) or externally influenced (e.g. achieving recognition) (Locke and Latham, 2019). Relatedly, clear and measurable goals in sports foster a sense of purpose and progress, enhancing an athlete's drive to pursue a goal (Healy et al., 2018; Jeong et al., 2023).

Finally, Flow Theory (Csikszentmihalyi, 1990) defines a flow state as an autotelic experience that is inherently enjoyable and intrinsically rewarding. Flow Theory is special in sport psychology as it concerns a state of mind that athletes might experience *in* sports. When athletes experience a flow state, movements feel effortless and performance becomes optimal (Jackson and Csikszentmihalyi, 1999). One of the principal preconditions to experiencing flow is that one's skills match the (physical) challenges of the activities, which results in *athletes' full engagement in their athletic performance that involves an ideal balance among focus, enjoyment, the challenges of the competitive situation and the athlete's skills.* (Carter et al., 2013).

Over the past four decades, Self-Determination Theory has established itself as one of the most influential theories on human motivation, personality development and wellness (Ryan and Deci, 2018g) in psychology and beyond [e.g. (Tyack and Mekler, 2020)]. SDT and its mini theories merge many aspects of human motivation in one unifying framework that links to established motivation frameworks. Its strength lies in its ability to integrate the internal psychological states of an athlete with their external environment (Standage, 2012; Standage and Ryan, 2020). Therefore, for the current paper, SDT provides a comprehensive and actionable framework that encapsulates the key elements of the above-described theories while also considering the athlete's broader social context. Section 4 will elaborate on how SDT integrates and expands upon these concepts in data-driven sports motivation. Before that, in the next section, we will illustrate how incorporating technology into sports broadens the complexity of motivation in sports.

3.2. Role of sports tracking in sports and sport motivation

Over the past years, sports tracking technology, which ranged from wearables to sophisticated data analytics, each playing a unique role in shaping an athlete's performance landscape (Liebermann et al., 2002; Vidal et al., 2021; Mencarini et al., 2022) has significantly influenced the way athletes train, compete and stay motivated (Haake, 2009; Dyer, 2015). Athletes can now monitor their athletic performance, track their progress and set personalized, specific and achievable goals through technology.

Currently, there are various forms of collecting sports data that help athletes manage their physical and mental well-being. For example, activity trackers (e.g. smart watches or fitness trackers) facilitate monitoring athletes' physiological responses, like stress levels (Rapp and Tirabeni, 2020), sleep quality (Simim et al., 2020) and estimated recovery times, which is essential for sports activity monitoring (Lee et al., 2017). Examples expand with recommender systems that help marathon runners manage their training load and can help them improve their performance (Berndsen et al., 2020). Through real-time posture and technique-related feedback (Schiewe et al., 2020), such systems help runners analyse and evaluate their running technique-related measurements (Kiss et al., 2017). All these possibilities provide insights into fitness levels and recovery suggestions and help reduce overuse-related injuries (Dellaserra et al., 2014). With those developments, it is now easier for athletes to make lifestyle adjustments and ensure that they are in optimal shape for training and competition (Rapp and Tirabeni, 2020).

Sports tracking also facilitates evidence-based training, allowing athletes to make data-driven decisions about their training and training plans (Mencarini et al., 2019). Performance data analysis instantly facilitates observing correlations between specific training practices and their outcomes, enabling athletes to tailor their training plans more effectively (Halson, 2014; West et al., 2021; Feely et al., 2023). Besides, data-driven training personalization optimizes athletic performance and ensures that athletes remain motivated even when they face physical and mental challenges (Rapp and Tirabeni, 2020). For example, Wozniak et al. (Wozniak et al., 2018) envisioned that sport data can provide athletes with 'reference points' to compare their performance and reflect upon. They argued that using data would enhance athletes' overall experience in participating sports. Such self-reflection, when managed positively, can be a significant motivational factor.

Gamification is generally used as an external element for motivating individuals (Knaving et al., 2018; Postma et al., 2023). However, for the sports context, the data and the gamification elements may also foster intrinsic motivation. For example, Bentvelzen et al. (2022) found that gamified social sports platforms like Zwift foster 'fair' competition while engaging in virtual cycling activity in a (geographically) distributed fashion. The same study reported the motivational effects of seeing the live trend of several cycling-related metrics (e.g. speed and cadence) on cyclists. Knaving et al. (Knaving et al., 2018) indicate that even highly motivated sporters can find a gamification system relevant to their sports training, which can provide motivation and quantifiable sports goals.

Reviewing one's physical activity data and seeing the achievement goals was found to help individuals plan their upcoming activities (Niess et al., 2021). On the other hand, playing sports is a relaxing activity for many individuals, and Knaving et al. (2015) argue that building interactive systems that support only the sports *goals* might undermine the sporters' internal motivations for doing sports. Receiving exclusive data and feedback about the sports practice might be perceived to be against the values of sporting challenges that athletes wish to experience in sports like climbing (Mencarini et al., 2016).

Rapp and Tirabeni (Rapp and Tirabeni, 2018) found that sport data can enlighten elite athletes about the correlation between various bodily sensations and specific physiological states (e.g. particular heart rate zone). Leveraging these findings, in our recent study, we discovered that not only do elite athletes reflect on their sensations through objective measures, but also non-elite athletes can 'guess' the measured metrics (e.g. heart rate) without checking their sports trackers (Karahanoğlu et al., 2024).

In their work, Mencarini et al. (Mencarini et al., 2019) delve into the diverse roles that wearables play in supporting athletes across various levels of expertise. Ultimately, they question whether wearables may be over-quantifying the sports experience while transforming physical activities into analysable digital data. This question can also be extended to examining the subjective experience and psychological impacts of sport data on athletes. Despite its numerous benefits, tracking sport data also presents challenges that athletes need to consider. For example, tracking risks focusing too heavily on quantifiable aspects of performance, resulting in negative self-attention while engaging in data (Eikey et al., 2021) and potentially neglecting subjective factors like motivation.

Overemphasis on data can lead to a reductionist view of sports performance, leading to an unhealthy obsession with or 'being emotionally invested in' numbers (Mopas and Huybregts, 2020; Snooks et al., 2022). Besides, the technology may not always provide an accurate or complete representation of performance, and constant monitoring can increase pressure on athletes (Palsa and Mertala, 2023), leading to anxiety, stress, feeling overwhelmed and confusion (Coşkun and Karahanoğlu, 2023). Due to the complexity of some metrics presented to athletes, these insights may not always be translated into actionable insights (Bentvelzen et al., 2023b). Knowing that every aspect of their performance is being tracked can be daunting and may detract the athletes from the

TABLE 1. Six Mini Theories of SDT and Their Relations to Motivational Roles of Sport Data

Mini Theory	*The theory . . .*	*This paper benefits from the theory to . . .*
Basic Psychological Needs Theory (BPNT)	Explains three basic psychological needs (i.e, autonomy, competence, and relatedness) and the interplay between them (Ryan and Deci, 2017; Ryan and Deci, 2018a; Vansteenkiste et al., 2020).	Reflect on the motivational roles of sport data in athletes' experience and flourishing.
Relationships Motivation Theory (RMT)	Discusses the relationship between autonomy and relatedness needs (Ryan and Deci, 2018f).	
Cognitive Evaluation Theory (CET)	Addresses intrinsic motivation in human flourishing and how external events, rewards and feedback can foster or thwart intrinsic motivation (Vansteenkiste et al., 2006; Ryan and Deci, 2017; Ryan and Deci, 2018c).	Illustrate how sport data works like an external factor for fostering and thwarting intrinsic motivation.
Organismic Integration Theory (OIT)	Explains how individuals internalise extrinsic motivation (Ryan and Deci, 2002; Ryan and Deci, 2017; Ryan and Deci, 2018e).	Explain the causal relations between an athlete's actions and the sport data as the outcome of these actions.
Causality Orientations Theory (COT)	Illustrates four extrinsic motivation regulation processes (Ryan and Deci, 2018b).	
Goal Contents Theory (GCT)	Explore why individuals engage in goals and aspirations and how different life goals impact people's motivation and overall well-being (Deci and Ryan, 2000; Ryan and Deci, 2017; Ryan and Deci, 2018d).	Articulate how sport data functions as part of intrinsic (e.g. growth) and extrinsic (e.g. fame) goals and to support the well-being of athletes.

joy and spontaneity of sports. These lead us to further unpack the motivational and experiential aspects of sport data from the lens of Self-Determination Theory.

4. SPORT DATA AND SELF-DETERMINATION THEORY

Self-Determination Theory (SDT) and its six mini theories investigate people's perceptions of the world, meaning attributions and emotional experiences, with underlying mechanisms involved in healthy self-organization (Ryan and Deci, 2017). It focuses on understanding and explaining the situational and contextual factors that support or thwart the functions of these underlying mechanisms essential to one's life. We argue that sport data is one of those new contextual factors that facilitate or undermine healthy human functioning within the context of sports. Because sport data includes various performance metrics, statistics and feedback gathered before, during and after training or competition, SDT and its mini theories provide insights into how sport data shapes motivation in sports. Table 1 provides an overview of these mini theories and how our paper benefits from them. Next, we will zoom in on and benefit from the mini theories of SDT to articulate and reflect on the roles of sport data in athletes' (1) flourishing, (2) intrinsic sport motivation, (3) sport motivation regulation and (4) sports goals and aspirations.

4.1. Roles of sport data in athlete flourishing

Basic Psychological Needs Theory (BPNT) concerns psychological needs and their relation to psychological health, well-being and optimal functioning. BPNT holds that needs are innate, psychological and organismic necessities that individuals need to fulfill for personal growth to occur (Ryan and Deci, 2000b). Individuals have three basic psychological needs (Table 2): *autonomy*, *competence* and *relatedness,* and when satisfied, these needs contribute to overall human well-being (Ryan and Deci, 2018a). Satisfaction of basic needs is highly relevant in sporting experiences, as satisfaction can increase voluntariness in sports experience and prevent athlete burnout, negative affect, exhaustion, depression and psychological arousal (Standage, 2012).

First, *autonomy* is one's ability to control, choose and self-regulate one's experiences and activities (Ryan and Deci, 2017). The fulfilment of the need for autonomy is supported by offering meaningful choice and structure while reducing the influence of controlling factors such as completion-contingent rewards (e.g. the rewards given after a task is completed) and controlling self-talk (e.g. internal dialogue that controls the behaviour of human being, often as a mirror of external pressures) (Ryan and Deci, 2017).

We see that sport data supports *autonomy* by offering flexibility and variability (i.e. choice) in sports training practice. This is seen in the form of data-driven workout suggestions and personalization of practice (Nylander and Tholander, 2016; Katharina Willamowski et al., 2022). Sport data, however, is also involved in undermining autonomy, as rewarding mechanisms related to using sport data harm autonomy (see 4.2 for further explanation). Furthermore, the in-act monitoring of sport data can enforce performance norms and invite external perceived locus of causality when individuals feel that they need to exercise at pre-determined (often well-rounded) intensity levels (Karahanoğlu et al., 2021).

Second, *competence* is the feeling of being effective in ongoing interactions with one's environment and being capable in one's activities (Ryan and Deci, 2002; Ryan and Deci, 2017). It can be thwarted very quickly when the activity is too challenging, or the individual receives personal criticism about the outcome of an activity (Ryan and Deci, 2017). In sports context, competence is found to energize individuals' sporting experience, motivate them to master their activities and not 'fall behind' (Pelletier et al., 1995; Podlog and Eklund, 2006).

Sport data may interact with *competence* in various ways. It enables athletes to draw (meaningful) comparisons either in terms of their past performances (aligning more with a mastery mindset) or in comparison to others (aligning more with a performance mindset). Sport data may also help athletes in seeking an optimal challenge. With vast amounts of sport data publicly available, athletes are enabled to find routines, training plans and (virtual) adversaries that offer an optimal level of challenge. This optimal level of challenge is highly individual

TABLE 2. Basic Needs and Their Relations with Sport Data in Athlete Flourishing

	Definition	*Sport Data may foster the basic need through*	*Sport Data may undermine the basic need through*
Autonomy	One's ability to self-control, choose and self-regulate their experiences and activities	• Flexibility and variability sports training practice • Data-driven workout suggestions • Personalisation of sports practice	• Over-rewarding the athlete • Enforcing performance norms • Controlling training choices too much rather than offering room for negotiation and own choice
Competence	Feeling of being effective in ongoing interactions with one's environment and being capable in one's activities	• Facilitating meaningful comparisons • Foster seeking optimal challenge and performance	• Creating criticism about under-performance or performance decline
Relatedness	Being connected to others and cared for by loved ones	• Sharing data publicly with others, staying connected	• Creating concerns and ruminations about social judgement and criticism

and depends, amongst others, on the athlete's mindset (Nicholls, 1984; Dweck, 1986).

Third, *relatedness* is the need to feel connected to others and cared for by loved ones (Ryan and Deci, 2017). To satisfy the need for relatedness, it is equally important to experience oneself as both giving to and receiving from others (Ryan and Deci, 2018g). Relationships Motivation Theory (Ryan and Deci, 2018f) further highlights the importance of the connection between relatedness and autonomy needs, such that receiving autonomy support from related partners facilitates emotional reliance on them. Yet, poorer quality relationships may result from the misalignment between relatedness and autonomy, resulting in conditional reliance in social relations (e.g. *only if you do this, I will do that*).

Sport data can also support *relatedness*. Numerous sports apps allow athletes to publicly share their sport data, which shapes the sports experience when the athlete is in the moment and when the activity is over. For some, sharing sports activity data on social platforms emerges from the need to receive the support and approval of others (Stragier et al., 2015), or responding to what others share may contribute in other ways to their own perceived fulfilment of a need for relatedness. For others, sharing live data offers a means to stay connected to their loved ones at home. For example, several sports watches enable the live sharing of heart rate data, location, speed and other metrics from which loved ones at home may derive that their significant other is doing well on long trails.

Beyond sharing data, SportsHCI research explored more profound ways of supporting relatedness by creating data-driven social support networks that rely on more than immediate peer comparisons (Mueller et al., 2010; Daiber et al., 2013; Curmi et al., 2017). Wozniak et al. (Wozniak et al., 2015), for instance, created an application that enables family and close friends to actively support long-distance runners on their trials rather than merely 'following their metrics from a distance'. However, sport data may also subvert the sense of relatedness: Ruminating about judgements related to sports performance data might negatively affect intrinsic motivation. This might be a way of craving external validation, leading to a 'dark pattern of relatedness'. For example, one might become dependent on positive feedback or need to show off and perceive that other people are envious of one's performance. Sharing sport data but not getting any response might also negatively impact the sense of relatedness.

4.2. Roles of sport data in intrinsic sport motivation

Cognitive Evaluation Theory (CET) deals with intrinsic motivation. It explains how the social context (e.g. social sports platforms), external factors (e.g. data-driven rewards) and activity-dependent feedback (e.g. performance data) support or thwart intrinsic motivation (Vansteenkiste et al., 2006; Ryan and Deci, 2017; Ryan and Deci, 2018c). Accordingly, intrinsic motivation is enhanced when individuals have different choices and feel a sense of control over their activities.

CET articulates that *autonomy* and *competence* are the primary antecedents of intrinsic motivation, and intrinsically motivated individuals are more likely to experience higher satisfaction than extrinsically motivated individuals (Ryan and Deci, 2000a). For intrinsically motivated individuals, performing a behaviour and moving towards new challenges is autonomous (Ryan and Deci, 2018e). Even though intrinsic motivation is not about the active pursuit of enjoyment, the reward of the behaviour is the *feeling of enjoyment* (Ryan and Deci, 2018g), which is a *by-product of full immersion in an activity* (Vansteenkiste et al., 2010). Such competence, in turn, promotes optimal activity engagement. In contrast, intrinsic motivation is undermined when individuals are presented with strict(er) rules or other controlling factors that reduce their sense of control in their activities (Vansteenkiste et al., 2006; Ryan and Deci, 2017; Ryan and Deci, 2018c). Based on these, we can illustrate various ways sports data interacts with the psychological need for autonomy and competence and influences intrinsic motivation (see Table 3 for illustrative examples and outcomes).

Sport data may promote or thwart the need for *autonomy* through external factors like *rewards* (Postma et al., 2023). For example, trophies, awards and virtual badges that sport data facilitates as an outcome of performance can enhance intrinsic motivation. At the same time, these external rewards might also thwart and undermine intrinsic motivation [see also: (Ryan and Deci, 2000c)]. Sport data may thwart the need for autonomy through (imposed) goals and the threat of punishment. For example, recent research showed that athletes may feel the need to 'hit the numbers' when wearing a tracker during sports (Karahanoğlu et al., 2021). This effect is strengthened when performance is framed in terms of normative evaluations, such as *you should run 60 minutes at 5:00 to have training benefit* or *this exercise did not have sufficient intensity and duration to have a training effect*. The feeling of constant evaluation even prompted a countermovement among

TABLE 3. Effects of Sport Data on Intrinsic Motivation

Related Basic need	*Examples of supporting/thwarting influence of sport data*	*Potential outcomes*
Autonomy	Trophies, awards and virtual badges that sport data facilitates as an outcome of performance Streak badges (i.e. no award if exercise streak is broken)	+ Self-satisfaction + Feeling of enjoyment—Reduce self-value and self-enjoyment
Competence	Personal records (e.g. predicted personal best time of half marathon) Skill-balancing mechanics Data-driven non/constructive messages	+ Sense of control and mastery + Fun, engagement, and self-esteem—Demoralizing—Loss of control over their sporting journey and achievements

runners[4], resulting in athletes sometimes abandoning their sports watches (Mertala and Palsa, 2023).

The work of (Deci et al., 1999) explains how the above-described shift results from sport data: even though rewards can be appealing, they can be detrimental to internal motivation and negatively impact interest and free-choice behaviour. Thus, external gratification might negatively affect intrinsic motivation (Weinberg and Gould, 2023). For example, even if an athlete is intrinsically motivated to perform (Matosic and Cox, 2014), an over-controlled way of using rewards and feedback about sports performance thwarts athletes' intrinsic motivation. An example would be the number of athletes an athlete was surpassed by (i.e. negative competence feedback).

Sport data may promote the need for *competence* through self-directed learning and motivational feedback which enhances athlete's sense of control (see Table 3 for illustrative examples and outcomes). For example, providing the recorded and predicted 'personal bests' enhances an athlete's sense of mastery (e.g. *you can do this!*). Meanwhile, sports technology can help athletes seek out optimal challenges by (virtually) connecting them to athletes worldwide with similar skill sets or abilities. Especially, 'hidden balancing' techniques show promise in promoting fun, engagement and self-esteem (Postma et al., 2022).

Still, how data-driven feedback is delivered can significantly impact an athlete's sense of competence. Negative feedback can be demoralizing, especially if not constructive or delivered without sensitivity to the athlete's effort and improvement. Communicating data-driven insights to support learning and growth is crucial, rather than merely highlighting deficiencies. Finally, athletes might feel their competence is under constant surveillance if their performance data is continuously monitored, analysed and discussed without consent or involvement. This can lead to a sense of loss of control over their sporting journey and achievements.

4.3. Roles of sport data in sport motivation regulation

Cognitive Evaluation Theory (COT) explains that individuals' motivational orientations are shaped by the causal relations between individuals' actions and the outcomes of these actions (Ryan and Deci, 2018b). It provides a more nuanced framework for explaining the different types of extrinsic motivation and deals with the dynamics of extrinsic motivation. It hypothesizes that satisfaction of the three basic psychological needs fosters the internalization of values and beliefs (Ryan and Deci, 2002; Ryan and Deci, 2018e). The drive to satisfy basic psychological needs can lead to six distinct behaviour regulation orientations (i.e. amotivation, external regulation, introjected regulation, regulation through identification, integrated regulation and intrinsic regulation-Table 4). Autonomy, competence and relatedness impact behaviour to varying degrees and Organismic Integration Theory (OIT) regards these regulation styles as a continuum. Through these regulation styles, a behaviour can later be internalized. Therefore, these regulation types are fundamental to understanding the value of extrinsic motivation in satisfying basic psychological needs.

Motivational orientations shape the athlete's behaviour and experience as well. For example, a swimmer who voluntarily engages with their stroke metrics during swimming has intrinsic motivation to use sport data, as they recognize the importance of monitoring their swimming technique. On the other hand, when they engage with those metrics just because they are motivated to please their coach, they show a more extrinsic motivation to use sport data.

Of the regulation types, *amotivation,* perhaps the least relevant regulation type for sport data, describes the state in which individuals see no value or interest in the behaviour, possibly partially due to their perceived incompetence (Ryan and Deci, 2018e). For those individuals, sport data can have neither an intrinsic nor extrinsic role in driving sports experience (see Table 4 for exemplar athlete thoughts in sport data use).

Among the four extrinsic motivation regulation styles, ***external regulation*** is the least autonomous form of extrinsic motivation that relies on external behaviour controllers (Ryan and Deci, 2018e). External regulation works best to reverse diminished self-determination and uses sport data as a means to an end; data-driven behaviour regulation, such as external rewards, punishments, or regulations, becomes the motivational element (e.g. athletes track sport data because their coach sets performance targets).

Introjected regulation, on the other hand, involves a form of extrinsic motivation characterized by internalized controls and is tied explicitly to affective and self-esteem contingencies. Individuals under introjected regulation may engage with sport data to avoid shame (e.g. hiding specific metrics from training summaries for self-pride) or to seek validation from other athletes (e.g. sharing training summaries for the attention of the general public for seeking worth).

Identified regulation signifies extrinsic motivation that has been embraced as personally valued and essential. This regulation style can integrate the sport data as external regulation with individuals' self-concept, goals and values, resulting in more self-determined and autonomous motivations (e.g. understanding performance data to set realistic goals aligned with their values of well-being).

Finally, ***integrated regulation*** represents the highest level of internalization along the continuum. Extrinsic motivation in

[4] https://www.brusselstimes.com/554554/are-you-on-strava-more-runners-ditch-technology-for-naked-experience Retrieved on 9 February 2024

TABLE 4. Sport data as Sports Behaviour Regulation Element (Produced based on Ryan and Deci (Ryan and Deci, 2018e))

Motivation	*Regulation style*	*Causality*	*Regulatory process*	*Athlete thoughts on sport data use*
Amotivation	Non-regulation	Impersonal	Nonintentional, no interest	Sport data has no value in helping me with my goals.
Extrinsic Motivation	External Regulation	External	External rewards and punishments	I use sport data because my coach sets performance goals.
	Introjected Regulation	Somewhat external	Self-control, ego-involvement	I use sport data to control/maintain a sense of pride and self-worth.
	Identified Regulation	Somewhat internal	Personal importance	I use sport data because it helps me value my well-being.
	Integrated Regulation	Internal	Awareness	I use sport data because it helps prevent overuse injuries.
Intrinsic Motivation	Intrinsic Regulation	Internal	Interest, enjoyment	I use sport data because I enjoy tracking my sports performance.

integrated regulation involves fully self-endorsed behaviours that reflect a high degree of personal autonomy (e.g. being immersed in data analytics to achieve peak performance and avoid overtraining).

Using regulation styles and orientations might put the athletes at risk of developing data-driven irrational beliefs about themselves. Such beliefs affect athletic performance and mental well-being (Turner, 2016) (e.g. *I must achieve the exact performance goals set by sport data analysis*), which places overly disruptive self-worth on validating what the data tells. For example, power or cadence meters can easily detect the cadence of a cyclist (i.e. revolutions per minute) and provide feedback about targeted values (e.g. 70–100 revolutions per minute also see: Ansley and Cangley (Ansley and Cangley, 2009)). Cyclists might be enticed to alter their stride to reach the optimal value and achieve the 'cadence goals' while interacting with their data. However, such optimal values are mostly misleading and insensitive to contextual factors, such as incline, terrain and weather conditions (Ansley and Cangley, 2009). As such, the ideal or optimal cadence value from an experiential perspective is different (e.g. 70 revolutions per minute) from a high-adopted optimal value, which causes forced cycling patterns that distract the cyclist from the sporting experience.

In short, even though the real-time data enables athletes to meticulously control their effort according to external goals (i.e. performance goals), such practices might negatively influence enjoyment. Similar irrational beliefs resulting from the sport data experience (e.g. *I cannot do this* or *I am worthless*) may lead to overtraining and metrics-focused inexpedient behaviour.

4.4. Roles of sport data in sport goals and aspirations

Goal Contents Theory (GCT) explores why individuals engage in goals and aspirations and how different life goals impact people's motivation and overall well-being (Vansteenkiste et al., 2006; Ryan and Deci, 2018d). Not all goals are equally important to pursue (Ryan et al., 1996) and attaining some goals will satisfy basic psychological needs more than others (Ryan and Deci, 2018d). GCT tackles goal attainment from the value-expectancy perspective, which states that people's goal adoption is affected by the expected value of the goal achievement. These values can have intrinsic (e.g. personal growth) or extrinsic (e.g. fame and image) aspirations (Ryan et al., 1996). Empirical findings show that the more an individual prioritizes extrinsic goals, the lower their well-being outcomes will be, as pursuing intrinsic goals satisfies basic psychological needs more than extrinsic goals (Ryan et al., 2008; Ryan and Deci, 2018d).

GCT highlights the importance of different types of goals (i.e. performance and growth) on motivation and well-being. Sport data plays a vital role in setting meaningful goals and assisting the athletes with insights into their performance in-act and progress in practice. It can work like an instrument that shapes and affects goal prioritization for athletes and assists them in setting and achieving goals effectively. It further helps athletes set short-term and long-term goals in their sporting endeavours, enabling them to contemplate and make informed decisions about their goal progress (Locke and Latham, 2019). Sport data also makes the achievability of goals visible to athletes. This allows more intricate goals (e.g. keeping minimal deviation in orienteering (Nylander and Tholander, 2016)) that require high-level planning.

In contrast, sport data may lead to goal-related negative consequences. For example, setting performance goals that are too challenging can harm physical performance (Kingston and Wilson, 2008; Swann et al., 2021). As such, heavily relying on data-driven and quantitative goals can create anxiety and rumination in goal pursuit [see (Ekhtiar et al., 2023)] . Unrealistic expectations driven by the use of sports data in-act and practice can lead to athletes neglecting their body's limitations and their embodied well-being in sports. For example, constant data monitoring and analysis can lead to increased risk of training decisions that lead to (potential for) harm. Impulsive, well-rounded, quantitative sporting goals, such as 'running a marathon under four hours' or 'completing a straight 10 kilometres', shape the way the sport data is experienced.

Hence, properly framing goals [e.g. (Ekhtiar et al., 2023)] ensures athletes are not overly fixated on limited numbers. First, they should make their decisions well –and not only– based on data. Second, having more focus (also) on intrinsic aspects of their performance and growth could help them listen to their body and make better-calibrated decisions, not just through data but also through a deep understanding of their body.

Emphasizing intrinsic motivation, focusing on individual differences and recognizing sports' broader pleasures and benefits beyond numerical achievements can help create a more positive and fulfilling sports experience. This might be why recreational runners have a particular goal to foster the use of specific technology (e.g. heart rate monitor in running). In contrast, the use of technology can discontinue after achieving goals, as athletes may not see a benefit in being invested in data after goal achievement (Mertala and Palsa, 2023).

5. DISCUSSION

So far, we have demonstrated that sport data has multiple intrinsic and extrinsic roles in sporting experience through the lens of Self-Determination Theory (SDT). We articulated how the SDT mini-theories can contribute to further understanding an athlete's various positive and negative experiences with and through sport data. We illustrated that sport data can enhance but also thwart sports motivation. But how can we deliberately design the use of sport data for it to be experienced with less negative consequences or to positively alter the sports experience *in-act* or *in-practice*? To tackle these questions, we will provide five emerging discussion points and related design implications to help future Sports-HCI research: (1) supporting athletes' self-value, (2) assessing the long-term impacts of sport data, (3) re-qualifying the sports experience, (4) moving beyond screens and (5) towards unpacking *sport data experience (SDX)*.

5.1. Supporting athletes' self-value

We highlighted that the obsession with sport data (Westlake, 2020) and the attitude towards hitting the numbers (Mopas and Huybregts, 2020; Karahanoğlu et al., 2021) have a real impact on sport participation. Irrational beliefs emerging from contemplating performance metrics can thwart an athlete's autonomy and competence (see Section 4.3, (Turner, 2016; Ryan and Deci, 2018b)). On the other hand, treating oneself kindly (i.e. self-compassion) can reduce emotional distress in sports (Ceccarelli et al., 2019). For example, several female hormone-related challenges that female athletes experience (e.g. menstruation disturbances, energy deficit and low bone density (Stand, 2007; Barrack et al., 2013; Adam et al., 2022)) are not yet addressed in SportsHCI, which can be detrimental to female athlete motivation. Hence, SportsHCI should highlight that performance progress is not linear (Den Hartigh et al., 2022) and that setbacks are also part of sports and gameplay.

Loerakker et al. (Loerakker et al., 2024) found that self-compassion is critical in shaping how individuals perceive and react to their data. They observed that the tone of the data visualizations (e.g. positive, neutral and negative) affects people's self-compassion, indicating that creating visualizations with empathy and insight can enhance positive interactions with personal data. They argued that self-compassion may help decrease self-criticality and rumination, often an unintended side effect of performance-focused tracking tools. In line with these, we argue that sport data can also result in self-devaluation and self-critique, which can thwart intrinsic sports motivation.

One way to overcome such attitudes and beliefs is to support athletes' self-value and self-care by balancing objective and subjective sports measures. Rather than solely focusing on the milestones and achievements through sport data, SportsHCI could focus more on discovering ways to foster athletes' self-appreciation (Elvitigala et al., 2024). These ways can be celebrating the flow and enjoyment in sports (e.g. feeling one has enjoyed and appreciated nature in sports (Mueller and Young, 2018)) or pleasant exhaustion rather than acknowledging the excessive pain. We believe such ways of acknowledging determination, perseverance and appreciation (e.g. *I kept going* or *I enjoyed it*), as much as top performance and personal bests (e.g. *I am good*) will foster the intrinsic motivation (as we discussed in 4.1 and 4.2; (Ryan and Deci, 2018a; Ryan and Deci, 2018c)) especially in athletes' *perceived fail* moments.

5.2. Assessing the long-term impacts of sport data

Feedback can be crucial for learning and task performance, depending on how it is framed and presented (Lam et al., 2011). We showed that it can also be harmful when it is centred on the self-level and is only for evaluating personal performance (i.e. *how good am I*?). On the other hand, it is perceived to be more constructive when the feedback is task-oriented and focused on the progress, process and improvement (i.e. *how do I improve*? Or *how can I keep going*?) (Lam et al., 2011). We argue that, in the context of sports, framing of feedback and sport data can lead to positive experiences as well as confrontational, cold and distant experiences. For example, from the lens of SDT [see Ryan and Deci, 2018d; Ryan et al., 1996], constantly highlighting a decreasing trend in an athlete's performance and emphasizing that they are not reaching their performance goals can be demotivating, when there is limited room for sports performance improvement (e.g. due to an acute injury, or ageing). We think such a context-insensitive way of using sport data in giving feedback undermines athletes' competence and intrinsic motivation.

On the other hand, we do not argue that sports technology should refrain from collecting data and providing feedback about athletes' mistakes and points of improvement. It already offers valuable insights and feedback, informs the athletes about their injury proneness or signals for overtraining and prevents potential sports participation precluding trends. The athletes should be well-informed that the efficacy of input data and the analysis heavily relies on their physiologies and skills.

The key point is that the interaction with sport data should be thoughtfully designed to inspire the athletes. Sport data will continue contributing to athletes' sensemaking of the data [e.g. (Coşkun and Karahanoğlu, 2023)] and modifying their lifestyle choices and sporting behaviours. Therefore, we argue that sports HCI should tackle a more caring and compassionate approach to support athletes in understanding their sports practice and exploring ways to maintain their long-term well-being.

5.3. Moving beyond the screens

We showed earlier that SportsHCI is beyond data collection in and about sports. The emerging challenge for SportsHCI is to shift the focus from developing tools to solely increase the data accuracy towards developing novel ways of addressing the subjective experiences related to sport data to motivate a variety of practices intrinsically. We argue that it is time for SportsHCI to refrain from the '*there is an app/dashboard for this*' approach and move beyond the screens to better support the basic psychological needs and intrinsic motivation of athletes. This challenge entails developing fresh and unconventional ways of communicating data.

Novel ways of data-driven feedback and reflection have already captivated the interest of various scholars. For example, (Restrepo et al., 2022) discuss creating balanced sports training through tangible reflection interfaces. Meanwhile, data physicalization (Jansen et al., 2015) has intrigued many HCI researchers. For example, 3D-printed objects (Khot et al., 2020) or the use of Legos (Bentvelzen et al., 2023a) to make the data understandable or memorable seem to work for this purpose (Bae et al., 2022). Additionally, sonification (i.e. sound as a way of data communication (van Rheden et al., 2020)) has emerged as a promising approach. Still, representing and communicating dynamic, multi-faced and life-long sport data representations remains challenging for SportsHCI.

Another way to move beyond the screens is to gain a deeper understanding of the psychological needs of athletes. In this paper, adopting an athlete-centred approach, we employed SDT to illustrate the gaps between what the data tells and how the athletes experience it. However, more research is needed to bridge the sports psychology and SportsHCI research domains. Recent attempts such as activity-centric design (Márquez Segura et al., 2016), towards teaching facilitation (Reidsma et al., 2022) and movement-based design (Vega-Cebrián et al., 2023) are good starting points to get to a more athlete and sports-centric way of designing for SportsHCI that moves away from a techno-solutionist orientation.

5.4. Re-qualifying subjective sporting experience

In Section 3, we showed that quantification of sports performance has fundamentally altered the act and practice of sports, and these alterations are not always for the better. In the act of sports, knowing about performance can be demotivating and frustrating, and these feelings can distract the athletes' attention from the experience of flow (Csikszentmihalyi and Jackson, 1999). For some athletes, satisfaction of basic needs like autonomy (i.e. self-regulating one's sports actions) and competence (i.e. dealing with the challenges of the sports activity) [see (Ryan and Deci, 2018a)] are more rewarding than performing to reach the quantifiable standards, which can overshadow the intrinsic joy of sports that initially attracts the athletes.

Meanwhile, the *qualified* self is a recent trend in self-tracking-related studies [e.g. (Van Koningsbruggen et al., 2022; Niess and Woźniak, 2018)]. It is about paying attention to lived bodily experiences over seemingly objective measures. Understanding and valuing these lived experiences can offer deeper insights than just meeting performance-based objectives. This way of thinking is also important for SportsHCI. For example, the same metrics (e.g. $\dot{V}O_2$ max) might have different connotations for different athletes (Karahanoğlu et al., 2024). Furthermore, athletes might experience the same data values differently: the exact value might represent a personal best for one and an absolute worst for someone else.

For us, it is of utmost importance to help athletes make their subjective interpretations by supporting subjective but trustworthy and meaningful data use experiences. Therefore, we call on SportsHCI researchers to explore the 'experience (re)qualification' and reactivate the view that the quality of the experience is as important as what the sport data concretely implies. We hope that SportsHCI will contemplate these subjectivities more often and abandon the view of accepting performance parameters as *the only important* measure of sports, thus embracing the subjectivity of the experiences.

5.5. Towards unpacking sport data experience (SDX)

Our arguments in the earlier sections illustrated that sport data may support or undermine the fulfilment of psychological needs and that it shapes athletes' regulation styles, motives and goals. Such use of sport data is not inherently harmful or detrimental to intrinsic motivation. Instead, it encourages athletes to choose whatever data fits their goals and motivations better. In our view, Self-Determination Theory (Ryan and Deci, 2000b; Ryan and Deci, 2017; Ryan and Deci, 2018g) offers an invaluable grounding for understanding these subjective experiences: what roles does the sport data take, and what drives the athletes to train for and engage in sports? In this paper, we explored the way sport data influences, affects and shapes the sports experience. Yet, the athletes' *sport data experience* (SDX) is not been fully explored yet. For example, one can experience moments of ecstasy when one achieves a target lactate threshold value after prolonged training; connectivity issues can result in frustration if data tracking is abruptly disrupted; the athlete's focus can be directed inwards through considering physiological measurement data. Sport data can be experienced as encouraging or as demanding, depending on circumstances. Contemplating the sport data itself can yield and incentivize a vast array of (novel) experiences.

We propose that Sport Data Experience (SDX) concerns the **subjective and multifaceted ways athletes interact with, perceive, and are influenced by sport data in the context of their training, performance and overall engagement with their sport**. It is shaped by several factors, including athletes' psychological needs, personal goals and motivations and the specific context in which the data is used and interpreted. This experience encompasses athletes' psychological, emotional and behavioural responses to collecting, analysing and interpreting sport data. The impact of SDX extends beyond mere numbers and statistics. We showed from the lens of SDT that it profoundly affects an athlete's behavioural and psychological state. Behaviourally, SDX can lead to adjustments in training intensity, technique modifications and even alterations in competitive strategies. SDX can boost confidence and motivation, while it might also challenge an athlete's self-esteem and resilience. Emotionally, athletes might experience joy upon achieving a personal best or frustration when data indicates underperformance.

Finally, we argue that the data is not the only way to the gold. We acknowledge that temporarily pausing sports tracking and not using sport data are also part of the game. Drawing parallel habits to many self-trackers [e.g. (Epstein et al., 2015)], athletes can choose to take a break from collecting data. Creating awareness that data is just a reflection tool and that our bodies are our source of data is crucial. Therefore, SportsHCI should focus more on boosting athletes' self-competence by helping athletes train more with their intuitions. Data's role in reflecting with intuition and learning to become better at listening to one's body could be highlighted more profoundly (Rapp and Tirabeni, 2018). This way, the Sport Data Experience (SDX) becomes a 'growth-oriented' (Dweck, 1986; Ryan and Deci, 2018d) recent journey to the self that contributes to the lifelong athlete's well-being.

6. CONCLUSIONS

In this paper, we defined sport data and its use in sporting performance by bridging SportsHCI studies with the insights we gain from Self-Determination Theory and sports psychology. We uncovered the intricate relations between the objective measures that sports technology provides and the resulting rise in motivational aspects for athletes. Our starting argument for this paper was to articulate that subjective experiences of sport data and the motivational aspects of it can go beyond performance metrics. We illustrated five emerging points of attention for SportsHCI to further investigate the effects of sport data on sports performance. In the end, we called for attention to the relations as an input, developing new tools and methods to unpack dimensions of Sport Data Experience beyond the data-driven feedback and screens. We hope that the research agenda we provide in this paper inspires further SportsHCI studies and elaborations on the thoughts we provide in this paper.

ACKNOWLEDGEMENTS

This manuscript has been completed after the SportsHCI Dagstuhl Seminar 23292. We would like to thank all the participants of the seminar for the inspiring talks that helped us shape the final version of this manuscript.

DATA AVAILABILITY

No new data were generated or analysed in support of this research.

REFERENCES

Adam, M. E. K., Bristow, A., Neely, K. C. and Erlandson, M. C. (2022). Do women athletes' experiences of menstrual function and dysfunction vary across competition levels? A mixed methods exploration. *Psychol. Sport Exerc.*, **63**, 1–6. https://doi.org/10.1016/j.psychsport.2022.102270.

Ansley, L. and Cangley, P. (2009). Determinants of "optimal" cadence during cycling. *Eur. J. Sport Sci.*, **9**, 61–85. https://doi.org/10.1080/17461390802684325.

Bae, S. S., Zheng, C., West, M. E., Do, E. Y.-L., Huron, S. and Szafir, D. A. (2022). Making data tangible: A cross-disciplinary design space for data physicalization. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '22)*, Article 81, pp. 1–18. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3491102.3501939.

Barrack, M. T., Ackerman, K. E. and Gibbs, J. C. (2013). Update on the female athlete triad. *Curr. Rev. Musculoskelet. Med.*, **6**, 195–204. https://doi.org/10.1007/s12178-013-9168-9.

Bentvelzen, M., Savino, G.-L., Niess, J., Masthoff, J. and Wozniak, P. W. (2022). Tailor my zwift: how to design for amateur sports in the virtual world. *Proc. ACM Hum.-Comput. Interact.*, **6**, 1–23. https://doi.org/10.1145/3546751.

Bentvelzen, M., Dominiak, J., Niess, J., Henraat, F. and Woźniak, P.W. (2023a). How Instructional Data Physicalisation Fosters Reflection in Personal Informatics. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*, Article 158, pp. 1–15. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3544548.3581198.

Bentvelzen, M., Niess, J. and Woźniak, P. W. (2023b). Designing reflective derived metrics for fitness trackers. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, **6**, 1–19. https://doi.org/10.1145/3569475.

Berndsen, J., Smyth, B. and Lawlor, A. (2020). Fit to run: Personalised recommendations for marathon training. In *Proceedings of the Proceedings of the 14th ACM Conference on Recommender Systems (RecSys '20)*, pp. 48–55. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3383313.3412228.

Carter, L., River, B. and Sachs, M. L. (2013). Flow in sport, exercise, and performance: a review with implications for future research. *J Multidiscip Res*, **5**, 17–32.

Ceccarelli, L. A., Giuliano, R. J., Glazebrook, C. M. and Strachan, S. M. (2019). Self-compassion and psycho-physiological recovery from recalled sport failure. *Front. Psychol.*, **10**, 1564. https://doi.org/10.3389/fpsyg.2019.01564.

Chatham, A. and Mueller, F. F. (2013). Adding an interactive display to a public basketball hoop can motivate players and foster community. In *Proceedings of the Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '13)*, pp. 667–676. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/2493432.2493478.

Clancy, R. B., Herring, M. P., MacIntyre, T. E. and Campbell, M. J. (2016). A review of competitive sport motivation research. *Psychol. Sport Exerc.*, **27**, 232–242. https://doi.org/10.1016/j.psychsport.2016.09.003.

Coşkun, A. and Karahanoğlu, A. (2023). Data sensemaking in self-tracking: towards a new generation of self-tracking tools. *International Journal of Human–Computer Interaction*, **39**, 2339–2360. https://doi.org/10.1080/10447318.2022.2075637.

Csikszentmihalyi, M. (1990). *Flow: The Psychology of Optimal Experience*. Harper & Row, New York.

Csikszentmihalyi, M. and Jackson, S. A. (1999). *Flow in sports: The keys to optimal experiences and performances*. Human Kinetics, Champaign, IL.

Curmi, F., Ferrario, M. A. and Whittle, J. (2017). Biometric data sharing in the wild: investigating the effects on online sports spectators. *Int. J. Hum. Comput. Stud.*, **105**, 56–67. https://doi.org/10.1016/j.ijhcs.2017.03.008.

Daiber, F., Kosmalla, F. and Krüger, A. (2013). BouldAR: using augmented reality to support collaborative boulder training. In *Proceedings of the CHI '13 Extended Abstracts on Human Factors in Computing Systems (CHI EA '13)*, pp. 949–954. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/2468356.2468526.

Deci, E. L. and Ryan, R. M. (2000). The" what" and" why" of goal pursuits: human needs and the self-determination of behavior. *Psychol. Inq.*, **11**, 227–268. https://doi.org/10.1207/S15327965PLI1104_01.

Deci, E. L., Koestner, R. and Ryan, R. M. (1999). A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation. *Psychol. Bull.*, **125**, 627–668. https://doi.org/10.1037/0033-2909.125.6.627.

Dellaserra, C. L., Gao, Y. and Ransdell, L. (2014). Use of integrated technology in team sports: a review of opportunities, challenges, and future directions for athletes. *J Strength Cond Res*, **28**, 556–573. https://doi.org/10.1519/JSC.0b013e3182a952fb.

Den Hartigh, R. J., Meerhoff, L. R. A., Van Yperen, N. W., Neumann, N. D., Brauers, J. J., Frencken, W. G., Emerencia, A., Hill, Y., Platvoet, S. and Atzmueller, M. (2022). Resilience in sports: a multidisciplinary, dynamic, and personalized perspective. *Int. Rev. Sport Exerc. Psychol.*, 1–23. https://doi.org/10.1080/1750984X.2022.2039749.

Duda, J. L. (1989). Relationship between task and ego orientation and the perceived purpose of sport among high school athletes. *J Sport Exerc Psychol*, **11**, 318–335. https://doi.org/10.1123/jsep.11.3.318.

Dweck, C. S. (1986). Motivational processes affecting learning. *Am. Psychol.*, **41**, 1040. https://doi.org/10.1037/0003-066X.41.10.1040.

Dyer, B. (2015) The controversy of sports technology: a systematic review. *Springerplus*, **4**, 1–12.

Eikey, E. V., Caldeira, C. M., Figueiredo, M. C., Chen, Y., Borelli, J. L., Mazmanian, M. and Zheng, K. (2021). Beyond self-reflection: introducing the concept of rumination in personal informatics. *Pers. Ubiquit. Comput.*, **25**, 601–616. https://doi.org/10.1007/s00779-021-01573-w.

Ekhtiar, T., Karahanoğlu, A., Gouveia, R. and Ludden, G. (2023). Goals for Goal Setting: A Scoping Review on Personal Informatics. In *Proceedings of the Proceedings of the 2023 ACM Designing Interactive Systems Conference (DIS '23)*, pp. 2625–2641. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3563657.3596087.

Elvitigala, D. S. *et al.* (2024). Grand Challenges in SportsHCI. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*24), May 11–16, 2024, Honolulu, HI, USA, pp. 22. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3613904.3642050.

Epstein, D. A., Ping, A., Fogarty, J. and Munson, S. A. (2015). A lived informatics model of personal informatics. In *Proceedings of the Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '15)*, pp. 731–742. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/2750858.2804250.

Feely, C., Caulfield, B., Lawlor, A. and Smyth, B. (2023). Modelling the Training Practices of Recreational Marathon Runners to Make Personalised Training Recommendations. In *Proceedings of the Proceedings of the 31st ACM Conference on User Modeling, Adaptation and Personalization (UMAP '23)*, pp. 183–193. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3565472.3592952.

Haake, S. J. (2009). The impact of technology on sporting performance in Olympic sports. *J. Sports Sci.*, **27**, 1421–1431. https://doi.org/10.1080/02640410903062019.

Halson, S. L. (2014). Monitoring training load to understand fatigue in athletes. *Sports Med.*, **44**, 139–147. https://doi.org/10.1007/s40279-014-0253-z.

Harwood, C. G., Keegan, R. J., Smith, J. M. J. and Raine, A. S. (2015). A systematic review of the intrapersonal correlates of motivational climate perceptions in sport and physical activity. *Psychol. Sport Exerc.*, **18**, 9–25. https://doi.org/10.1016/j.psychsport.2014.11.005.

Havlucu, H., Coşkun, A. and Özcan, O. (2019). Specifying Relevant Textural Properties for Unobtrusive Feedback on Sports Performance. In *Proceedings of the Thirteenth International Conference on Tangible, Embedded, and Embodied Interaction (TEI '19)*, pp. 165–171. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3294109.3300974.

Healy, L., Tincknell-Smith, A. and Ntoumanis, N. (2018). Goal setting in sport and performance. In Healy, L., Tincknell-Smith, A. and Ntoumanis, N. (eds) *Oxford Research Encyclopedia Of Psychology*. Oxford University Press. https://doi.org/10.1093/acrefore/9780190236557.013.152.

Jackson, S. A. and Csikszentmihalyi, M. (1999). *Flow in Sports*. Human Kinetics, United States of America.

Jansen, Y., Dragicevic, P., Isenberg, P., Alexander, J., Karnik, A., Kildal, J., Subramanian, S. and Hornbæk, K. (2015). Opportunities and challenges for data physicalization. In *Proceedings of the Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*, pp. 3227–3236. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/2702123.2702180.

Jeong, Y. H., Healy, L. C. and McEwan, D. (2023). The application of goal setting theory to goal setting interventions in sport: a systematic review. *Int. Rev. Sport Exerc. Psychol.*, **16**, 474–499. https://doi.org/10.1080/1750984X.2021.1901298.

Jowett, G. E., Hill, A. P., Hall, H. K. and Curran, T. (2016). Perfectionism, burnout and engagement in youth sport: the mediating role of basic psychological needs. *Psychol. Sport Exerc.*, **24**, 18–26. https://doi.org/10.1016/j.psychsport.2016.01.001.

Karahanoğlu, A., Gouveia, R., Reenalda, J. and Ludden, G. (2021). How are sports-trackers used by runners? Running-related data, personal goals, and self-tracking in running. *Sensors*, **21**, 3687. https://doi.org/10.3390/s21113687.

Karahanoğlu, A., Coskun, A., Postma, D., Scheltinga, B. L., Gouveia, R., Reidsma, D. and Reenalda, J. (2024). Is it just a score? Understanding Training Load Management Practices Beyond Sports Tracking. In *Proceedings of the Conference on Human Factors in Computing Systems (CHI '24)*, May 11–16, 2024, Honolulu, HI, USA, p. 18. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3613904.3642051.

Katharina Willamowski, J., Gonzalez-Jimenez, S., Legras, C. and Gallo, D. (2022). FlexNav: flexible navigation and exploration through connected runnable Zones. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '22)*, Article 368, pp. 1–17. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3491102.3502051.

Khot, R. A., Hjorth, L. and Mueller, F. (2020). Shelfie: a framework for designing material representations of physical activity data. *ACM Transactions on Computer-Human Interaction (TOCHI)*, **27**, 1–52. https://doi.org/10.1145/3379539.

Kingston, K. and Wilson, K. (2008). The application of goal setting in sport. In *Advances in Applied Sport Psychology: A Review*, pp. 75–123. Routledge.

Kiss, F., Kucharski, K., Mayer, S., Lischke, L., Knierim, P., Romanowski, A. and Wozniak, P. W. (2017). RunMerge: Towards enhanced proprioception for advanced amateur runners. In *Proceedings of the Proceedings of the 2017 ACM Conference Companion Publication on Designing Interactive Systems (DIS '17 Companion)*, pp. 192–196. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3064857.3079144.

Knaving, K., Wołniak, P., Fjeld, M. and Björk, S. (2015). Flow is Not Enough: Understanding the Needs of Advanced Amateur Runners to Design Motivation Technology. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*, pp. 2013–2022. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/2702123.2702542.

Knaving, K., Woźniak, P. W., Niess, J., Poguntke, R., Fjeld, M. and Björk, S. (2018). Understanding grassroots sports gamification in the wild. In *Proceedings of the Proceedings of the 10th Nordic Conference on Human–Computer Interaction (NordiCHI '18)*, pp. 102–113. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3240167.3240220.

Kondric, M., Sindik, J., Furjan-Mandic, G. and Schiefler, B. (2013). Participation motivation and student's physical activity among sport students in three countries. *J. Sports Sci. Med.*, **12**, 10–18.

Kuru, A. (2016) Exploring experience of runners with sports tracking technology. *Int. J. Hum. Comput. Interact.*, **32**, 847–860. https://doi.org/10.1080/10447318.2016.1202461.

Lam, C. F., DeRue, D. S., Karam, E. P. and Hollenbeck, J. R. (2011). The impact of feedback frequency on learning and task performance: challenging the "more is better" assumption. *Organ. Behav. Hum. Decis. Process.*, **116**, 217–228. https://doi.org/10.1016/j.obhdp.2011.05.002.

Le Foll, D., Rascle, O. and Higgins, N. C. (2008). Attributional feedback-induced changes in functional and dysfunctional attributions, expectations of success, hopefulness, and short-term persistence in a novel sport. *Psychol. Sport Exerc.*, **9**, 77–101. https://doi.org/10.1016/j.psychsport.2007.01.004.

Lee, E. C., Fragala, M. S., Kavouras, S. A., Queen, R. M., Pryor, J. L. and Casa, D. J. (2017). Biomarkers in sports and exercise: tracking health, performance, and recovery in athletes. *J. Strength Cond. Res.*, **31**, 2920–2937. https://doi.org/10.1519/JSC.0000000000002122.

Liebermann, D. G., Katz, L., Hughes, M. D., Bartlett, R. M., McClements, J. and Franks, I. M. (2002). Advances in the application of information technology to sport performance. *J. Sports Sci.*, **20**, 755–769. https://doi.org/10.1080/026404102320675611.

Lochbaum, M. R. and Roberts, G. C. (1993). Goal orientations and perceptions of the sport experience. *J. Sport Exerc. Psychol.*, **15**, 160–171. https://doi.org/10.1123/jsep.15.2.160.

Locke, E. A. and Latham, G. P. (1990). *A Theory of Goal Setting & Task Performance*. Prentice Hall, Englewood Cliffs, NJ..

Locke, E. A. and Latham, G. P. (1994). Goal setting theory. In *Motivation: Theory and Research*, pp. 13–29. Prentice Hall, Englewood Cliffs, NJ.

Locke, E. A. and Latham, G. P. (2019). The development of goal setting theory: a half century retrospective. *Motivation Science*, **5**, 93–105. https://doi.org/10.1037/mot0000127.

Locke, E. A., Shaw, K. N., Saari, L. M. and Latham, G. P. (1981). Goal setting and task performance: 1969–1980. *Psychol. Bull.*, **90**, 125–152. https://doi.org/10.1037/0033-2909.90.1.125.

Loerakker, M. B., Niess, J., Bentvelzen, M. and Woźniak, P. W. (2024). Designing data Visualisations for self-compassion in personal informatics. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, **7**, 1–22. https://doi.org/10.1145/3631448.

Márquez Segura, E., Waern, A., Márquez Segura, L. and López Recio, D. (2016). Playification: the physeear case. In *Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play (CHI PLAY '16)*, pp. 376–388. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/2967934.2968099.

Matosic, D. and Cox, A. E. (2014). Athletes' motivation regulations and need satisfaction across combinations of perceived coaching behaviors. *J. Appl. Sport Psychol.*, **26**, 302–317. https://doi.org/10.1080/10413200.2013.879963.

McAuley, E. and Duncan, T. E. (2014). The causal attribution process in sport and physical activity. In Graham, S. and Folkes, V. (eds) *Attribution Theory: Applications to Achievement, Mental Health, and Interpersonal Conflict*. Psychology Press, NY, USA.

McClelland, D. (2015). Achievement motivation theory. In *Organizational Behavior 1*. Routledge.

McCormick, A., Meijen, C., Anstiss, P. A. and Jones, H. S. (2019). Self-regulation in endurance sports: theory, research, and practice. *Int. Rev. Sport Exerc. Psychol.*, **12**, 235–264. https://doi.org/10.1080/1750984X.2018.1469161.

Mencarini, E., Leonardi, C., De Angeli, A. and Zancanaro, M. (2016). Design opportunities for wearable devices in learning to climb. In *Proceedings of the Proceedings of the 9th Nordic conference on human–computer interaction (NordiCHI '16)*, Article 48, pp. 1–10. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/2971485.2971509.

Mencarini, E., Rapp, A., Tirabeni, L. and Zancanaro, M. (2019) Designing wearable systems for sports: a review of trends and opportunities in human–computer interaction. *IEEE Trans. Hum. Mach. Syst.*, **49**, 314–325. https://doi.org/10.1109/THMS.2019.2919702.

Mencarini, E., Rapp, A., Colley, A., Daiber, F., Jones, M. D., Kosmalla, F., Lukosch, S., Niess, J., Niforatos, E. and Woźniak, P. W. (2022). New trends in HCI and sports. In *Proceedings of the Adjunct Publication of the 24th International Conference on Human–Computer Interaction with Mobile Devices and Services (MobileHCI '22)*, Article 6, pp. 1–5. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3528575.3551426.

Menheere, D., Lallemand, C., Van Der Spek, E., Megens, C., Vande Moere, A., Funk, M. and Vos, S. (2020). The runner's journey: identifying design opportunities for running motivation technology. In *Proceedings of the Proceedings of the 11th Nordic Conference on Human–Computer Interaction: Shaping Experiences, Shaping Society (NordiCHI '20)*, Article 79, pp. 1–14. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3419249.3420151.

Mertala, P. and Palsa, L. (2023) Running free: recreational runners' reasons for non-use of digital sports technology. *Sport Society*, **27**, 329–345. https://doi.org/10.1080/17430437.2023.2246408.

Mopas, M. S. and Huybregts, E. (2020) Training by feel: wearable fitness-trackers, endurance athletes, and the sensing of data. *Senses Soc.*, **15**, 25–40. https://doi.org/10.1080/17458927.2020.1722421.

Mueller, F. and Young, D. (2018) *10 Lenses to Design Sports-HCI*, vol. 12, pp. 172–2. Foundations and Trends® in Human–Computer Interaction. http://dx.doi.org/10.1561/1100000076.

Mueller, F. F., Vetere, F., Gibbs, M. R., Agamanolis, S. and Sheridan, J. (2010). Jogging over a distance: the influence of design in parallel exertion games. In *Proceedings of the 5th ACM SIGGRAPH Symposium on Video Games (Sandbox '10)*, pp. 63–68. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/1836135.1836145.

Nicholls, J. G. (1984) Achievement motivation: conceptions of ability, subjective experience, task choice, and performance. *Psychol. Rev.*, **91**, 328–346. https://doi.org/10.1037/0033-295X.91.3.328.

Niess, J. and Woźniak, P. W. (2018). Year supporting meaningful personal fitness: the tracker goal evolution model. In *Proceedings of the CHI '18: CHI Conference on Human Factors in Computing Systems (CHI '18)*, Paper 171, pp. 1–12. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3173574.3173745.

Niess, J., Woźniak, P. W., Abdelrahman, Y., ElAgroudy, P., Abdrabou, Y., Eckerth, C., Diefenbach, S. and Knaving, K. (2021). 'I don't need a goal': attitudes and practices in fitness tracking beyond WEIRD user groups. In *Proceedings of the Proceedings of the 23rd International Conference on Mobile Human–Computer Interaction (MobileHCI '21)*., Article 15, pp. 1–14. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3447526.3472062.

Nylander, S. and Tholander, J. (2016). Drifting off course: how sports technology can use real-time data to add new dimensions to sports. In *Proceedings of the Proceedings of the 15th International Conference on Mobile and Ubiquitous Multimedia (MUM '16)*, pp. 1–4. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3012709.3012740.

Ogles, B. M. and Masters, K. S. (2000). Older vs. younger adult male marathon runners: participative motives and training habits. *J. Sport Behav.*, **23**, 130.

Palsa, L. and Mertala, P. (2023). Contextualizing everyday data literacies: the case of recreational runners. *Int. J. Hum. Comput. Interact.*, 1–12. https://doi.org/10.1080/10447318.2023.2241612.

Pelletier, L. G., Tuson, K. M., Fortier, M. S., Vallerand, R. J., Briere, N. M. and Blais, M. R. (1995). Toward a new measure of intrinsic motivation, extrinsic motivation, and amotivation in sports: the sport motivation scale (SMS). *J. Sport Exerc. Psychol.*, **17**, 35–53. https://doi.org/10.1123/jsep.17.1.35.

Podlog, L. and Eklund, R. C. (2006). A longitudinal investigation of competitive athletes' return to sport following serious injury. *J. Appl. Sport Psychol.*, **18**, 44–68. https://doi.org/10.1080/10413200500471319.

Postma, D. B., van Delden, R. W., Koekoek, J. H., Walinga, W. W., van Hilvoorde, I. M., van Beijnum, B. J. F., Salim, F. A. and Reidsma, D. (2022). *A Design Space of Sports Interaction Technology*, Vol. 15: No. 2–3,, pp. 132–316. Foundations and Trends® in Human–Computer Interaction. http://dx.doi.org/10.1561/1100000087.

Postma, D., Karahanoğlu, A., Delden, R. v. and Reidsma, D. (2023). The cost of reward: a critical reflection on the 'what', 'how', and 'why' of gamification for motivation in sports. In *Proceedings of the Companion Proceedings of the Annual Symposium on Computer-Human Interaction in Play (CHI PLAY Companion '23)*, pp. 222–224. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3573382.3616102.

Rapp, A. and Tirabeni, L. (2018). Personal informatics for sport: meaning, body, and social relations in amateur and elite athletes. *ACM Trans. Comput.-Hum. Interact.*, **25**, 1–30. https://doi.org/10.1145/3196829.

Rapp, A. and Tirabeni, L. (2020). Self-tracking while doing sport: comfort, motivation, attention and lifestyle of athletes using personal informatics tools. *Int. J. Hum. Comput. Stud.*, **140**, 102434. https://doi.org/10.1016/j.ijhcs.2020.102434.

Reidsma, D., Delden, R. W. v., Weijdom, J. P., Hansen, R. E., Lekbo, S., Andersen, R. V., Rasmussen, L. S. R. and Elbæk, L. (2022). Considerations for (Teaching) Facilitator Roles for Movement-Based Design. In *Proceedings of the Extended Abstracts of the 2022 Annual Symposium on Computer-Human Interaction in Play (CHI PLAY '22)*, pp. 233–239. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3505270.3558315.

Restrepo, J., Vos, S., Verhagen, E. and Lallemand, C. (2022). Hyaku: A qualitative negotiation-through-interaction interface to support runners in achieving balanced training sessions. In Lockton, D., Lenzi, S. and Hekkert, P. (eds) *DRS2022: Bilbao*, 25 June - 3 July, Bilbao, Spain. https://doi.org/10.21606/drs.2022.569.

van Rheden, V., Grah, T. and Meschtscherjakov, A. (2020). Sonification approaches in sports in the past decade: a literature review. In *Proceedings of the 15th International Audio Mostly Conference (AM '20)*, pp. 199–205. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3411109.3411126.

Rockmann, R. (2019). Don't hurt me . . . no more? An empirical study on the positive and adverse motivational effects in fitness apps. In *Proceedings of the 27th European Conference on Information Systems (ECIS)*, Stockholm & Uppsala, Sweden, June 8-14, 2019. ISBN 978-1-7336325-0-8 Research Papers. https://aisel.aisnet.org/ecis2019_rp/90.

Ryan, R. M. and Deci, E. L. (2000a). Intrinsic and extrinsic motivations: classic definitions and new directions. *Contemp. Educ. Psychol.*, **25**, 54–67. https://doi.org/10.1006/ceps.1999.1020.

Ryan, R. M. and Deci, E. L. (2000b). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *Am. Psychol.*, **55**, 68–78. https://doi.org/10.1037/0003-066X.55.1.68.

Ryan, R. M. and Deci, E. L. (2000c). When rewards compete with nature: The undermining of intrinsic motivation and self-regulation. In *Intrinsic and Extrinsic Motivation: The Search for Optimal Motivation and Performance*, pp. 13–54. CA Academic Press, San Diego.

Ryan, R. M. and Deci, E. L. (2002) Overview of self-determination theory: An organismic dialectical perspective. In Ryan, R. M. and Deci, E. L. (eds) *Handbook of Self-Determination Research*, pp. 3–33. University of Rochester Press, Rochester.

Ryan, R. M. and Deci, E. L. (2017). *Self-Determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness*. The Guilford Press A Division of Guilford Publications, Inc., New York.

Ryan, R. and Deci, E. (2018a). Basic psychological needs theory: satisfaction and frustration of autonomy, competence and relatedness in relation to psychological wellness and full functioning. In *Self Determination Theory: Basic Psychological Needs in Motivation, Development and Wellness*. Guilford Press, United States of America.

Ryan, R. and Deci, E. (2018b) Causality orientations theory: individual differences in, and priming of motivational orientations. In *Self Determination Theory: Basic Psychological Needs in Motivation, Development and Wellness*. Guilford Press, United States of America.

Ryan, R. and Deci, E. (2018c). Cognitive evaluation theory, part I: the effects of rewards, feedback, and other external events on intrinsic motivation. In *Self Determination Theory: Basic Psychological Needs in Motivation, Development and Wellness*. Guilford Press, United States of America.

Ryan, R. and Deci, E. (2018d). Goal contents theory: aspirations, life goals, and their varied consequences. In *Self Determination Theory: Basic Psychological Needs in Motivation, Development and Wellness*. Guilford Press, United States of America.

Ryan, R. and Deci, E. (2018e). Organismic integration theory: internalization and the differentiation of extrinsic motivation. In *Self Determination Theory: Basic Psychological Needs in Motivation, Development and Wellness*. Guilford Press, United States of America.

Ryan, R. and Deci, E. (2018f) Relationships motivation theory: the self in close relationships. In *Self Determination Theory: Basic Psychological Needs in Motivation, Development and Wellness*. Guilford Press, United States of America.

Ryan, R. and Deci, E. (2018g). Self determination theory: an introduction and overview. In *Self Determination Theory: Basic Psychological Needs in Motivation, Development and Wellness*. Guilford Press, United States of America.

Ryan, R. M., Sheldon, K. M., Kasser, T. and Deci, E. L. (1996). All goals are not created equal: An organismic perspective on the nature of goals and their regulation. In Gollwitzer, P. M., Bargh, J. A. (eds), *The Psychology of Action: Linking Cognition and Motivation to Behavior*, pp. 7–26. Guilford Press, New York.

Ryan, R. M., Huta, V. and Deci, E. L. (2008). Living well: a self-determination theory perspective on eudaimonia. *J. Happiness Stud.*, **9**, 139–170. https://doi.org/10.1007/s10902-006-9023-4.

Savery, R., Ayyagari, M., May, K. and Walker, B. N. (2019). Soccer sonification: Enhancing viewer experience. In *Proceedings of the 25th International Conference on Auditory Display (ICAD 2019)*, pp. 207–213. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.21785/icad2019.037..

Schiewe, A., Krekhov, A., Kerber, F., Daiber, F. and Krüger, J. (2020). A study on real-time visualizations during sports activities on smartwatches. In *Proceedings of the Proceedings of the 19th International Conference on Mobile and Ubiquitous Multimedia (MUM '20)*, pp. 18–31. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3428361.3428409.

Senko, C., Hulleman, C. S. and Harackiewicz, J. M. (2011). Achievement goal theory at the crossroads: old controversies, current challenges, and new directions. *Educ. Psychol.*, **46**, 26–47. https://doi.org/10.1080/00461520.2011.538646.

Simim, M. A. D. M., Souza, H. D. S., Cardoso Filho, C. A., Gianoni, R. L. D. S., Bezerra, R. R., Affonso, H. D. O., Amadio, A. C., D'Almeida, V., Serrão, J. C. and Claudino, J. G. (2020). Sleep quality monitoring in individual sports athletes: parameters and definitions by systematic review. *Sleep Sci*, **13**, 267–285.

Sit, C. H. P. and Lindner, K. J. (2005). Motivational orientations in youth sport participation: using achievement goal theory and reversal theory. *Personal. Individ. Differ.*, **38**, 605–618. https://doi.org/10.1016/j.paid.2004.05.015.

Snooks, K., Whitham, R., Richards, D. and Lindley, J. (2022). Beyond the body: Moving past the metricised bodily goal in self-tracking. In Lockton, D., Lenzi, S., Lenzi, S., Hekkert, P., Oak, A., Sádaba, J. and Lloyd, P. (eds) *DRS2022: Bilbao*, June - 3 July, Bilbao, Spain. https://doi.org/10.21606/drs.2022.501.

Stand, P. (2007) The female athlete triad. *Med. Sci. Sports Exerc.*, **39**, 1867–1882. https://doi.org/10.1249/mss.0b013e318149f111.

Standage, M. (2012). Self-determination theory and performance in sport. In Murphy, S. (ed), *The Oxford Handbook of Sport and Performance Psychology*. Oxford University Press, USA.

Standage, M. and Ryan, R. M. (2020). Self-determination theory in sport and exercise. *Handbook of Sport Psychology*, 37–56. https://doi.org/10.1002/9781119568124.ch3.

Stragier, J., Evens, T. and Mechant, P. (2015). Broadcast yourself: an exploratory study of sharing physical activity on social networking sites. *Media International Australia*, **155**, 120–129. https://doi.org/10.1177/1329878X1515500114.

Swann, C., Rosenbaum, S., Lawrence, A., Vella, S. A., McEwan, D. and Ekkekakis, P. (2021). Updating goal-setting theory in physical activity promotion: a critical conceptual review. *Health Psychol. Rev.*, **15**, 34–50. https://doi.org/10.1080/17437199.2019.1706616.

Taylor, I. M., Boat, R. and Murphy, S. L. (2020). Integrating theories of self-control and motivation to advance endurance performance. *Int. Rev. Sport Exerc. Psychol.*, **13**, 1–20. https://doi.org/10.1080/1750984X.2018.1480050.

Turner, M. J. (2016). Rational emotive behavior therapy (REBT), irrational and rational beliefs, and the mental health of athletes. *Front. Psychol.*, **7**, 1423. https://doi.org/10.3389/fpsyg.2016.01423.

Turner, M. J. *et al.* (2022). "I must do this!": a latent profile analysis approach to understanding the role of irrational beliefs and motivation regulation in mental and physical health. *J. Sports Sci.*, **40**, 934–949. https://doi.org/10.1080/02640414.2022.2042124.

Tyack, A. and Mekler, E. D. (2020). Self-determination theory in hci games research: current uses and open questions. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*, pp. 1–22. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3313831.3376723.

Van Koningsbruggen, R., Shalawadi, S., Hornecker, E. and Echtler, F. (2022). Frankie: exploring how self-tracking technologies can go from data-centred to human-'centred (MUM '22). In *Proceedings of the 21st International Conference on Mobile and Ubiquitous Multimedia*, pp. 243–250. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3568444.3568470.

Vansteenkiste, M., Lens, W. and Deci, E. L. (2006) Intrinsic versus extrinsic goal contents in self-determination theory: another look at the quality of academic motivation. *Educ. Psychol.*, **41**, 19–31. https://doi.org/10.1207/s15326985ep4101_4.

Vansteenkiste, M., Niemiec, C. P. and Soenens, B. (2010). The development of the five mini-theories of self-determination theory: An historical overview, emerging trends, and future directions. In Urdan, T. C. and Karabenick, S. A. (eds) *The Decade Ahead: Theoretical Perspectives on Motivation and Achievement*, (Advances in Motivation and Achievement, Vol. 16 Part A), pp. 105–165. Emerald Group Publishing Limited, Leeds. https://doi.org/10.1108/S0749-7423(2010)000016A007.

Vansteenkiste, M., Ryan, R. M. and Soenens, B. (2020). Basic psychological need theory: Advancements, critical themes, and future directions. In *Motivation and Emotion*, 44, pp. 1–31. https://doi.org/10.1007/s11031-019-09818-1.

Vega-Cebrián, J. M., *et al.* (2023). Design resources in movement-based design methods: a practice-based characterization. In *Proceedings of the Proceedings of the 2023 ACM Designing Interactive Systems Conference (DIS '23)*, July 10–14, 2023, Pittsburgh, PA, USA, pp. 18. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3563657.3596036.

Vidal, L. T., Zhu, H., Waern, A. and Segura, E. M. (2021). The Design Space of Wearables for Sports and Fitness Practices. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*, Article 267, pp. 1–14. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3411764.3445700.

Vlachopoulos, S. P., Karageorghis, C. I. and Terry, P. C. (2000) Motivation profiles in sport: a self-determination theory perspective. *Res. Q. Exerc. Sport*, **71**, 387–397. https://doi.org/10.1080/02701367.2000.10608921.

Weinberg, R. S. and Gould, D. (2023). *Foundations of sport and exercise psychology*. Human kinetics, USA.

Weiner, B. (1985). An attributional theory of achievement motivation and emotion. *Psychol. Rev.*, **92**, 548–573. https://doi.org/10.1037/0033-295X.92.4.548.

Weiner, B. (2012a). An attribution theory of motivation. In VanLange, P. A. M., VanLange, P. A. M. and Higgins, E. T. (eds) *Handbook of Theories of Social Psychology*, Vol. 1, pp. 135–155. SAGE. https://doi.org/10.4135/9781446249215.n8.

Weiner, B. (2012b). *An Attributional Theory of Motivation and Emotion*. Springer Science & Business Media, NY, USA.

West, S. W., Clubb, J., Torres-Ronda, L., Howells, D., Leng, E., Vescovi, J. D., Carmody, S., Posthumus, M., Dalen-Lorentsen, T. and Windt, J. (2021). More than a metric: how training load is used in elite sport for athlete management. *Int. J. Sports Med.*, **42**, 300–306.

Westlake, E. J. (2020). If you see me collapse, pause my Strava. In Walsh, S. L. (ed) *Sporting Performances: Politics in Play*, pp. 130–147. Routledge, London. https://doi.org/10.4324/9780429265167-8.

Wozniak, P., Knaving, K., Björk, S. and Fjeld, M. (2015). Untangling running: designing for real-life runner experiences. *Interactions*, **22**, 40–43. https://doi.org/10.1145/2724584.

Wozniak, P., Colley, A. and Häkkilä, J. (2018). Towards increasing bodily awareness during sports with wearable displays. In *Proceedings of the Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers (UbiComp '18)*, pp. 738–741. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3267305.3267703.