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Contextualizing Everyday Data Literacies: The Case of Recreational Runners

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ABSTRACT

Data literacy is typically described in a decontextualized manner, and many data literacy frameworks are detached from the "messy" realities of everyday life. In the present study, we selected a specific context (recreational running), specific data technology (self-tracking devices), and specific viewpoint (accuracy of data and analyses) to construct a substantial theory of (one form of) contextual data literacy. The research question is: How does recreational runners' everyday data literacy appear in relation to the accuracy of measurements and analyses of self-tracking devices? Through an abductive analysis of qualitative survey data ($N = 1057$), we identified the data literacy actions that runners engaged with when assessing the accuracy of data in relation to their subjective needs, objectives, and life situations. The first-order data literacy actions (comparison and evaluation) captured how runners assessed and analyzed the accuracy of data, and they took place mainly in the immediate context of running. The second-order data literacy actions (acceptance, adaptation, and optimization) were the result of the runners' reflections on what they sought from running and how they valued data, as well as their broader life situation.

KEYWORDS
Data literacy; self-tracking; running; contextualization; wearables

1. Introduction

Data literacy has become a buzzword in recent scholarly discussions, with a steep increase in articles published since 2020 (Gebre, 2022; see also Cui et al., 2023; Ghodoosi et al., 2023).[1] Despite this volume, certain perspectives on data literacy appear to be emphasized more than others. Data literacy is often described in an abstract manner, and the increase in generalization is often made at the expense of contextual sensitivity by stressing only the components needed in any given context (Prado & Marzal, 2013). As a result, many data literacy frameworks are more or less detached from the "messy" realities of everyday life. Wolff et al. (2016), for instance, divided data-literate citizens into four broad categories: readers, communicators, makers, and scientists. As we are about to suggest, such a division does not necessarily capture the essence of everyday literacies. Pangrazio and Selwyn (2019, p. 10) criticized many existing data literacy frameworks for neglecting "the generative and emergent meanings the individual brings to personal data." Indeed, there have been calls for a more nuanced focus to understand the contextuality of data literacy (e.g., Markham, 2020; Michael & Lupton, 2016; Pangrazio & Selwyn, 2019; Pink et al., 2017; Prado & Marzal, 2013) because contextualization can provide "better understandings of how people make sense of data and incorporate them into their practices and concepts of selfhood and embodiment" (Pink et al., 2017, p. 2).

This article contributes to addressing this need by providing a contextualized view of everyday data literacy. The context, recreational running, is a highly digitized and datafied form of a popular leisure sport (Scheerder & Breedveld, 2015). According to Janssen et al. (2020), 87 percent of runners who participate in events[2] use technology, with sports watches being the most common choice. In Finland, a highly digitalized society, the use of tracking technology has even become a norm among runners (Mertala & Palsa, 2023; Tainio, 2020). Feng and Agosto (2019) described runners as power users of tracking technology, a label that many runners identify themselves with (Esmonde, 2020). Lupton et al. (2018) even suggested that when people use "digital devices for self-tracking, they become datafied assemblages that are moving through space. Bodies, space, and place are simultaneously digital-material" (2018, p. 648). In fact, runners can be located in all of Wolff et al. (2016) four categories: (1) they generate (make) data while they run; (2) they interpret (read) data to track their development (Feng & Agosto, 2019; Clegg et al., 2020); (3) they communicate with others by sharing their data via social media (Carlén & Maivorsdotter, 2017; Littlejohns et al., 2019); and (4) they act like scientists, as self-tracking sets up "a laboratory of the self" (Kristensen & Ruckenstein, 2018).

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Theoretically, our study is situated within the emerging field of relational literacy research (e.g., Burnett & Merchant, 2020), which acknowledges literacy as a complex assemblage of sociomaterial relations that are constantly remade (Budach et al., 2015). It also underscores the importance of adopting a "literacy-as-event" approach (Burnett & Merchant, 2020) that focuses on the interactions between people (in this case, recreational runners) and things (such as sports technologies) (Blackman & Venn, 2010). Methodologically, we align with Pink et al. (2017) in recognizing the potential of qualitative research for comprehending how people make meaning with and about data. Our methodological approach draws from the tradition of abductive analysis (Grönfors, 2011), emphasizing the use of empirical data (Clarke & Braun, 2013). Additionally, we engage in a cyclical interpretative analysis process (Lindgren et al., 2020), allowing for analytical comparisons within and between data and theory (Fram, 2013). The research question guiding our study is as follows:

- How does recreational runners' everyday data literacy appear in relation to the accuracy of measurements and analyses of self-tracking devices?

The article is structured as follows: First, we establish a theoretical foundation for the study by examining the significance of data and data literacy within the context of recreational running. We achieve this by combining running-specific themes with existing literature on (conceptual) data literacy. Next, we outline the methodology employed in our research. We present our findings, organized according to the main themes of data literacy actions and their relationships. Finally, we conclude the article by discussing and interpreting the findings in relation to existing frameworks and conceptualizations of data literacy.

2. Datafied runner and contextualized data literacy

Embodied knowledge—the cognitive evaluation of corporeal sensations and linked emotions—has traditionally played a major role in runners' meaning-making (Clegg et al., 2020; Hockey, 2013). However, running also has a long parallel history of technology-mediated performance measurement, especially at the elite level. In the early 20th century, runners, such as Paavo Nurmi, a nine-time Olympic winner, used training logs and analog stopwatches to record their training and evaluate their development (Kaila, 1925). During the past decades, the rapid development of mobile self-tracking devices, such as sports watches and smart watches, has made self-tracking technologies available for recreational runners, especially in developed countries (Feng & Agosto, 2019). At the time of writing this, there are more than 10,000 devices with running-specific features available in the sport technology market (Aliverti et al., 2022).

Technological development is not restricted to the ever-growing availability of numerous gadgets, but it has brought people in front of new epistemic situations with regard to their fitness and health. The most illustrative example is perhaps quantified self-movement, which aims to provide "self-knowledge through numbers" (Quantified Self, n.d.-a) that are obtained via self-tracking devices. Running and the quantified self are closely related. As stated on the Quantified Self webpage, "almost all runners are into quantified self (even if they don't yet know it) by measuring every time they run and then studying their stats" (Quantified Self, n.d.-b). Indeed, 20th-century runners use a wide range of technologies to access, store, and manage performance data, as well as various reflective ways for analyzing the data to identify longer-term trends and evaluate the need for changing their training practices (Feng & Agosto, 2019).

The practices of accessing, storing, managing, and analyzing data, as described by Feng and Agosto (2019), are frequently considered as various forms or components of data literacy (as discussed in the reviews by Cui et al., 2023; Gebre, 2022; Ghodoosi et al., 2023). For instance, Ridsdale et al. (2015) define data literacy as "the ability to collect, manage, evaluate, and apply data in a critical manner" (p. 8). Similar aspects are also encompassed in Prado and Marzal's (2013) influential article, which characterizes data literacy as involving understanding, obtaining, reading, interpreting, evaluating, managing, and utilizing data. While these definitions may have their own limitations, particularly in terms of technicality (see, Gebre, 2022), they provide a valuable conceptual foundation for examining human actions and agencies in various data practices, including those related to running.

Let us begin with data collection, management, and handling, which are considered subsets of data literacy in numerous frameworks across different disciplines (e.g., Burress et al., 2021; Carlson et al., 2011; Cui et al., 2023; Ghodoosi et al., 2023; Prado & Marzal, 2013; Vuorikari et al., 2022). We recognize that many sports technologies, particularly sports watches, enable users to export data in various formats (e.g., .tcx, .csv, .gpx) for personalized analyses and other purposes. For instance, a runner may download a .csv file and analyze it using software, such as Excel, R, or equivalent, or convert it (Ghodoosi et al., 2023) to other formats like JSON for further use. However, in the everyday context of sports technology, data collection, management, and handling typically occur in a highly automated manner with minimal effort required from the user. Sports watches initiate data collection (such as location, pace, and heart rate) with a single press of a button and upload the data to the cloud (e.g., Polar Flow, Garmin Connect) via a Bluetooth connection. Similarly, enabling two or more applications to share and analyze data can often be achieved simply by selecting a checkbox in the application's settings, thereby lacking the higher-order critical reflection that is often associated with data sharing (Clegg et al., 2020; Ghodoosi et al., 2023; Prado & Marzal, 2013).

In the context of recreational running, humans and their meaning-making practices enter the picture in the evaluation and application of the data. Critical evaluation is required because there are no USB ports in the human body and, thus, wearables typically rely on indicators of the phenomena they aim to capture and measure. Take cadence, the number of steps the runner takes in a minute, for example. If the runner is not using a foot pod, cadence is typically measured via an accelerometer from the movement of the runner's arm. Another example is wrist-based heart rate monitoring. Instead of measuring heartbeats per se, optical sensors assess the rise and fall of blood cell light absorption at the wrist to detect heart rate (Davis, 2021). Awareness of the indicative nature of data can be approached as understanding (Prado & Marzal, 2013) or identification of data (and its limits) (Pangrazio & Selwyn, 2019), both of which are commonly found in data literacy frameworks (Ghodoosi et al., 2023).

The indicative nature of the data raises questions about the accuracy, validity, and reliability of consumer-level wearable sports technologies—a topic that has been the subject of a notable amount of research (e.g., Johansson et al., 2020; Montes et al., 2020; Pobiruchin et al., 2017; Roos et al., 2017). Studies suggest that wearable technologies are relatively trustworthy, but that there are differences between devices and manufacturers (Fuller et al., 2020; Johansson et al., 2020; Roos et al., 2017), as well as within the different features of individual technology: the measurement of steps and heart rate monitoring can be more trustworthy than the evaluation of energy expenditure, for instance (Evenson et al., 2015; Fuller et al., 2020). Thus, in terms of data literacy, making informed conclusions and decisions requires critical evaluation of the data by the user (Cui et al., 2023; Ghodoosi et al., 2023; Prado & Marzal, 2013)

That being said, informed evaluation is not a simple and straightforward task. The (in)accuracy of tracking devices is not a static phenomenon, but accuracy varies with regard to the type of activity, geographical location, and the user's physical characteristics. The accuracy of wrist-worn devices tends to decrease as intensity increases (Pasadyn et al., 2019), which means that most loading exercises provide the most inaccurate data. Wrist-based heart rate monitors also react to the indicators of pulse change with a delay (Coros, 2022). This causes a mismatch between the real-time cardioload and the one informed by the watch in situations when the intensity of running changes either due to the type of exercise (i.e., interval training) or changes in terrain (i.e., uphill/downhill) or weather conditions (i.e., headwind/tailwind). Additionally, the wearer's skin color, including tattoos, can affect the quality of the signals of wrist-worn optical meters (Coros, 2022; Parak, 2018). GPS tracking, in turn, is less reliable in mountainous/hilly surroundings or in urban areas with tall buildings due to signal obstruction (Johansson et al., 2020; Vorlíček et al., 2021). These notions highlight the contextual and situational dimensions of data literacy ("literacy as event," see Burnett & Merchant, 2020), which have not been extensively addressed in data literacy frameworks and definitions, with only a few exceptions (Markham, 2020; Prado & Marzal, 2013).

Although measurement inaccuracy is a common reason to abandon self-tracking technologies (Attig & Franke, 2020; Nuss & Li, 2021) data and accuracy mean different things for different runners. Typically, the most interested in technology and data are those for whom running is "serious leisure" (Feng & Agosto, 2019; Kuru, 2016; Stebbins, 2017), which includes goal-oriented training and regular participation in competitions (Qiu et al., 2020; Tainio, 2020). Others may run for health-related reasons (Feng & Agosto, 2019; León-Guereño et al., 2021; Mertala & Palsa, 2023) and wish to monitor their activity levels and rest but do not need (or are interested in) as detailed and fine-grained metrics as more "serious" runners (see Clermont et al., 2020). Running can also be approached from a post-sport perspective, in which running is primarily an aesthetic experience instead of fitness (Atkinson, 2010; Feng & Agosto, 2019; Tainio, 2020), which arguably provides different stances toward technology and data (Mertala & Palsa, 2023; Tainio, 2020). We understand this variation to be about the relational and dynamic nature of peoples' agencies in relation to data (Clegg et al., 2020; Esmonde, 2020; Vartiainen et al., 2022): data and its accuracy are always reflected in relation to something (i.e., the subjective meaning of running), and the views can change over the course of time (i.e., when life situations enable or prevent more goal-oriented running).

3. The current study

3.1. Data and participants

The data were collected in the spring of 2021 as a qualitative web survey, which was shared on Finnish social media groups on running and endurance sports and on the authors' own social media profiles. The survey was also sent to individual running/sports clubs. The survey consisted of 10 questions. Background questions were used to collect information, such as the age, gender, and running/exercise activity (running/exercise sessions per week) of participants, but not individual contact or identifying information, such as name, address, or possible sports club. The more substance-related questions asked about the meaning of running and the kinds of technologies the respondents used (see Appendix for the full questionnaire). The study design required no ethical review from the Finnish National Board on Research Integrity (2019, p. 20). The study's data were generated from the responses to the following questions:

- How accurate and reliable do you consider the measurements and analyses of the technologies you use (e.g., distance, speed, heart rate, fitness tests and assessments, and personalized training programs)? Please justify your views.

One thousand and fifty-eight runners completed the survey. Table 1 illustrates the demographic background of the participants.

3.2. Analysis

The analysis process was divided into four phases: familiarization (Clarke & Braun, 2013), open coding, axial coding, and selective coding (Williams & Moser, 2019), which formed a cyclical process of abstraction, reorganization, and

Table 1. Demographic statistics of the participants.

Demographic statistics of the participants*		
Gender ($n = 1057$)	N	%
• Female	679	64
• Male	372	35
• Other	6	1
Age ($n = 941$)	N	%
• 20 or younger	3	0,5
• 21–30	101	11
• 31–40	286	30
• 41–50	345	37
• 51–60	173	18
• 61–70	29	3
• 71 or older	4	0,5
Weekly running activities ($n = 1037$)	N	%
• 0	6	1
• 1–2	231	22
• 3–4	555	54
• 5–6	199	19
• 7 or more	46	4

*Because all the questions were voluntary the number of responses per item differs from the number of respondents.

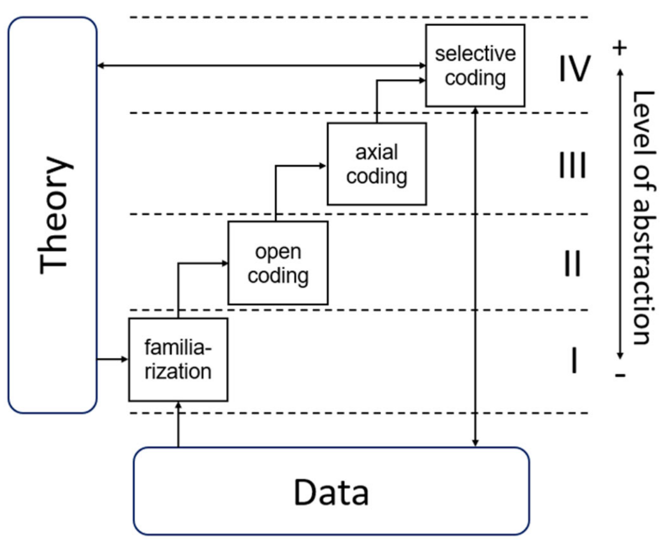

Figure 1. Summary of the four-phased abductive analysis process.

recontextualization, familiar in the qualitative research (Lindgren et al., 2020). Figure 1 summarizes the phases, which are discussed in detail below.

(I) In familiarization, the data was read through closely, and the inductive and literature-informed [e.g., the role of embodied knowledge (Clegg et al., 2020; Hockey, 2013), data evaluation and other common themes of data literacy frameworks (e.g., Cui et al., 2023; Ghodoosi et al., 2023)] initial notions were written down and discussed with the researchers. (II) Open coding was conducted for a randomly selected pilot dataset consisting of 100 responses. The aim of the open coding was to construct an initial classification scheme to use as a basis for coding the whole dataset. (III) During the axial coding phase, we synthesized the 48 codes identified via open coding and constructed an initial conceptual framework that contained five themes: *comparison, embodiment, evaluation, reflection, and optimization*. In selective coding, we compared the themes with the remaining data and theoretical literature to refine them and gain a better understanding of how they were related to each other. For example, the theme *embodiment* was re-formulated as a reference point for *evaluation* and *comparison* instead of a separate action. Even though embodiment played an important role in the data, it was addressed only in relation to other actions, for instance, by comparing the data with the embodied feeling (see also Clegg et al., 2020). The following data excerpt illustrates the way in which one runner compared the data about fitness levels with both other (technology-based) tests and embodied feelings.

> The fitness assessment is probably correct to some extent; at least, it correlates well with tests done elsewhere and with my own feelings, but the time estimates for different distances are far from accurate. (Runner 807)

(IV) During selective coding, two new themes—*acceptance* and *adaptation*—were formed. In addition, the framework was restructured by dividing the data literacy actions into two levels. *First-order data literacy actions* (comparison, evaluation) describe the ways in which runners explore and make sense of the accuracy of the data either in the immediate context (during running) or afterward but provide no information on how runners react to and act in regard to their notions. *Second-order data literacy actions* (acceptance, adaptation, and optimization) refer to the variety of actions the runners engaged in based on the notions made via first-order actions through the mediating action of *reflection*. Various extracts from the data are presented in the Findings section to improve the reliability and clarity of the analysis. Lastly, since not all readers are necessarily familiar with self-tracking devices and related software, we will use screenshots from our own running data to concretize the phenomenon the respondents described.

3.3. Limitations

Although recreational runners as power users of data technologies (Feng & Agosto, 2019; Janssen et al., 2020) form a well-justified group for studying peoples' everyday data literacies, the actual respondents were obtained through self-selective sampling (Heckman, 1990) and, thus, do not represent the whole population of runners. The limited amount of background information prevented us from examining the possible relationships between, for instance, the respondents' general technology use and their running-related data literacy actions.

4. Findings

> Heart rate as a wrist heart rate measurement does not feel reliable, especially in intervals, or on a cool day, in a t-shirt, when surface blood flow is reduced. That's why I also wear a heart rate belt. Even in the distance, you can see discrepancies between the two monitors. I'd like more accurate data and personalized training programs, but that will come a bit later when the baby grows, and I can run a bit better again. (Runner 56)

The excerpt above serves as an introduction to our main findings, the themes, and their relationships, which are summarized in Figure 2. Although the excerpt provides

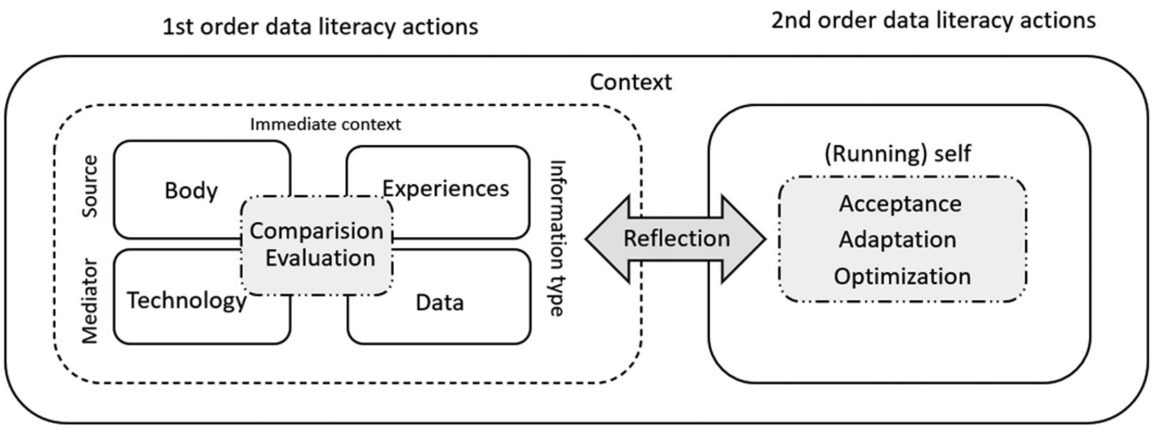

Figure 2. The main themes and their relationships.

examples of both first- and second-order data literacy actions, it is not a definite account and a more detailed description of each theme is provided in its own subsections.

First-order data literacy actions: The respondent used (cold) weather and the intensity of training as examples of situations in which wrist-based (optical) heart rate monitoring produced non-trustable data. Such notions were understood to be about the *evaluation* of the accuracy of the wearable trackers that take place in the *immediate context*. The respondent also wrote that she noticed that two monitors could provide different data about the mileage covered. Such notions were understood to be about the *comparison* of different information sources; in this particular case, the runner compared technology-mediated information from two sources and found them to be incoherent.

The respondent's pondering about her desire to obtain (even) more accurate data and personalized training programs and the realities of being a parent for a newborn child were categorized as a *reflection* of the relationship between data and the running self that takes place in the broader (and more complex) *context* of life. The outcomes of reflection were labeled *second-order data literacy actions*. The notion that the respondent also uses a chest strap to monitor her heart rate was understood to depict the *optimization* of technology use: because the respondent is aware that the accuracy of optical sensors is limited in certain weather conditions and training modes, she uses another technology (which she considers more accurate) in such situations. Since the (possible) new technology (which is hoped to provide more accurate data) leads to new comparisons and evaluations, the relationship between first- and second-order data literacy actions is more cyclical than sequential by nature.

4.1. First-order data literacy actions: Comparison and evaluation

4.1.1. Comparison

The comparison took place between different sources of information (comparing bodily and technology-mediated information; comparing the data provided by different technologies) as well as within the data (comparing the data from an individual exercise with the data collected cumulatively for a longer period of time) and were further divided into two strategies: conforming comparison and calibrative comparison.

In a *conforming comparison*, runners typically compared different sources of information. If there was correspondence, the data were deemed trustworthy. The following excerpt serves as an example of a conforming comparison that takes place between bodily experience and technology-mediated information: the runner compares bodily experiences and technology-mediated information in the real-time immediate context. More precisely, the runner compares the experienced heart rate with the measured one, notices that there is a correspondence between them, and considers heart rate monitoring to be trustworthy.

> I believe they are quite accurate […]. When I use only the heart rate and distance function of my device, I can compare my physical sensation during a run with the heart rate of my device. If I feel my heart rate is high and the device's heart rate is high, I feel confident in the device and consider it to be relatively accurate. (Runner 395).

The runners also compared the data from individual runs with the data accumulated over the course of time. They explained that if the data, at a general level, were uniform, it would be easy to identify possible errors in the data from individual sessions:

> On average, distance, pace, and heart rate (measured with a heart rate belt) are reliable. Although errors sometimes occur, they are distinguishable from the data. The assessment of credibility is based on the fact that the measurements can be compared with years of accumulated data on one's own fitness measured by different devices. (Runner 804)

The previous data excerpt is illustrative, as the runner explained that they compared the measurements not only with the accumulated dataset but also with data constructed with different devices. Comparing the data generated by different devices is a common way to address their accuracy. In the words of Runner 438, "Although different people have different devices, in general, easily verifiable data are easily comparable, and when the results confirm each other, they are reliable." In this case, the consistency between devices increases the runner's confidence in the data.

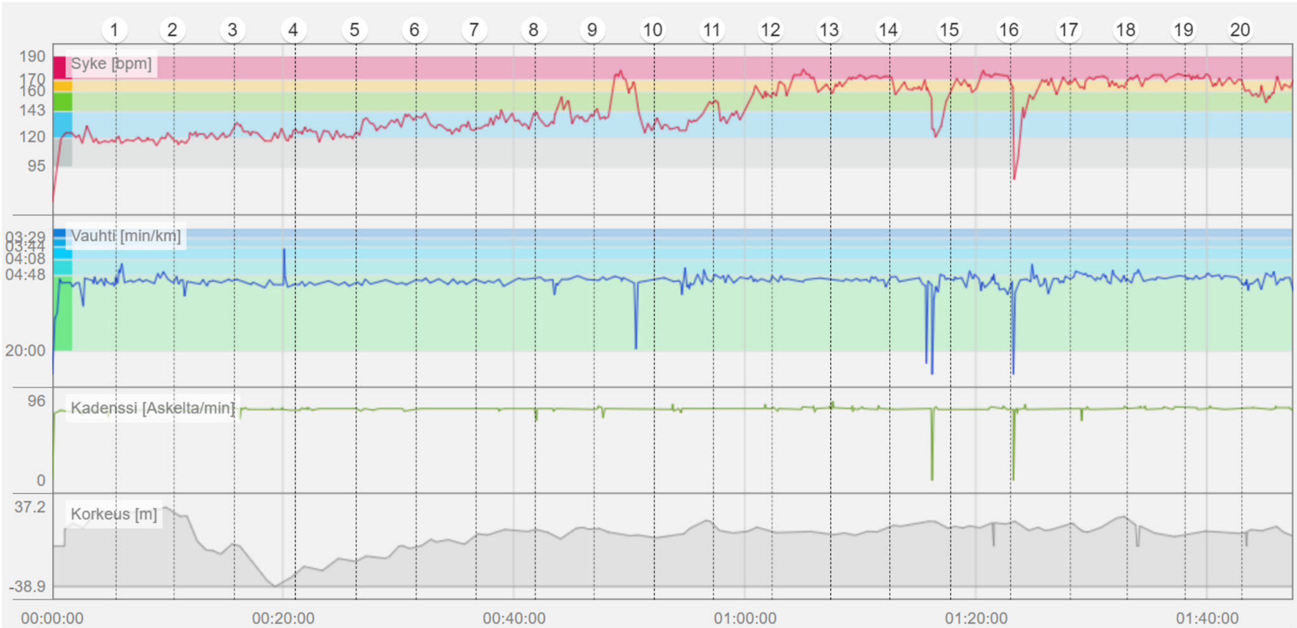

Figure 3. Cadence lock.

In a *calibrative comparison*, runners compared the technology they commonly used with other forms of measurement they considered legitimate. The legitimate measurements included laboratory tests, official routes, and more "high-end" consumer and professional technologies. Runner 36 participated annually in lactate level tests and said to keep his "own technology with me and compare[d] them to the devices/results of the test maker." If the data and results were similar, then everyday sports technology could be trusted. Runner 615 wrote about a similar case: "In the bicycle ergometer test, the heart rate monitor gave very similar results to the test equipment." However, on some occasions, no concrete comparison was required, even when the functional logic of the sports technology was considered sufficiently similar to a trusted one:

> I consider heart rate measurement to be quite accurate because the technology is similar to the oxygen saturation monitors used in hospitals. It goes up and down logically. (Runner 891)

4.1.2. Evaluation

Calibrative comparison is closely connected with *evaluation*: in calibrative comparison, one source of information or method of measurement is held more trustworthy than the other, which requires evaluation of different information sources. The evaluation also took place in situations where the runner doubted that there was something wrong with the data. A common example was that there was no correspondence between bodily experiences and technology-mediated information (often in an immediate real-time context), of which the following excerpt is an illustrative example:

> I've been running long enough to know my heart rate roughly by feel. Sometimes the watch will pull something of its own in terms of heart rate […] It's all about feeling and listening to your body. (Runner 106)

In the excerpt above, the runner says that their long history of running has taught them to identify the heart rate level (i.e., aerobic/anaerobic) based on the embodied sensations. Based on the "elaborated gut-feeling," the runner states that they can identify when the watch is "acting according to its own will" (instead of measuring the heart rate correctly), to cite their exact expression. Runner 656 provided a more detailed explanation. He stated, "I know whether my heart rate is cadence (a typical disorder) or something else just because my maximum heart rate is lower than my cadence." The phenomenon the runner referred to is known as the "cadence lock," in which the sports watch confuses the runner's cadence (or the movement of the runner's hand to be more precise) with their heart rate. As Davis (2021, n.p.) summarized:

> The heart rate signal at your wrist is tiny compared to the noise from the motion of your wrist! Thus, it's easy to see where "cadence lock" comes from: the watch locks onto the noise generated by the motion of your wrist, instead of the true signal generated by your heart.

Figure 3 provides an example of how a cadence lock appears in the data visualization of a tracker. As the figure shows, speed, cadence, and elevation remain rather static, but (the measured) heart rate jumps to around 170 beats per minute, first at the 9-kilometer mark and then for a longer term after kilometer 12. A closer inspection of the cadence data and heart rate data shows that the heart rate is approximately twice the cadence. This implies that the watch mistaken the movement of the arm as the heart rate.

4.2. Reflection as a mediator

Reflection refers to the process in which the runner reflects on the accuracy of the data in relation to what can be measured, and the runners' subjective relationship with running in a profound manner. Thus, reflection exceeds the immediate context and acts as a mediator between the first and second orders. By *reflection on what can be measured*, we mean that various respondents pondered what exactly can be tracked and measured and how accurate consumer-level technology can be in the first place. Runner 842 took a rather philosophical stance and commented that the data and analyses can never be "complete truths" because "a human is a bio-psycho-physical entity whose analysis is definitely an impossible task for only a sports watch." Here, she meant that sports watches, at best, can track and provide information about physical and biological performance. The psychological dimensions, such as the aesthetic experiences that running provides (e.g., Tainio, 2020), are out of the scope of these tools. Runner 757, in turn, had a more practical perspective, as he used the simplicity of the monitored phenomenon as a basis for a distinctive assessment.

> Distance, heart rate, and pace might be the easiest variables to monitor, but for example, in fitness tests and evaluations, there should be an indefinite number of parameters so that they could be useful? (Runner 757)

The logic here is quite straightforward: the simpler the phenomenon, the easier it is to measure (see also Sharon & Zandbergen, 2017), which improves the accuracy and reliability of the measurement. Indeed, pace—the rate of movement (e.g., 6 min per kilometer; Merriam-Webster, n.d.)—is a far less complicated phenomenon than (physical) fitness—the condition of being physically strong and healthy (Cambridge Dictionary, n.d.). The latter includes muscle strength, endurance, and general health, and needs to be evaluated with respect to the subject's age and gender, which results in the need for an "indefinite number of parameters" to cite Runner 757's own words.

Although the runners were aware of the limitations of the self-tracking devices they used, they differed in their stances toward the accuracy of data with regard to the *subjective meaning of running*. If the runners had no particular performance-related goals, they were happy to track their mileage or physically active hours in a cursory or vague manner. In other words, they *accepted* the shortcomings of the trackers and their features. Others, however, expressed that they wanted the data to be as accurate and/or useful as possible and approached this objective via two means, which we named *adaptation* and *optimization.*

4.3. Second-order data literacy actions: Acceptance, adaptation, and optimization

4.3.1. Acceptance

Rather than problematizing the lack of accuracy of data (or attempting to solve the associated challenges), many runners were at peace with the issue––a phenomenon we categorized as *acceptance.* The following excerpt exemplifies the ways in which the runners explicated being aware of the shortcomings of the data but were not bothered by the inaccuracy.

> The distance varies, and sometimes I make miraculous jumps up to 10 km. The heart rate comes in at a lag measured at the wrist but enough for a Sunday runner. Fitness tests are too positive, as are the promised marathon times. The program is easy and too positive—that is, too-good finish times—but I don't mind, since I am aware of that. (Runner 132)

The runner noted that her watch made errors in the immediate context of running (lag in heart rate monitoring, GPS errors) and gave overly optimistic fitness evaluations and race-time predictions. The runner, however, did not see them as major issues because she was aware of the bias and did not run with specific goals in mind; thus, the distorted data did not affect her decisions. She was not alone in her view: Runner 411 described that the errors in location tracking did not matter because, for them, running was about "a recreational sport of a coach potato." Runner 542, in turn, explained that accuracy and credibility did not make a difference if they were not about goal-oriented activities. However, the runner stated, "Anyway, the results are 'close enough' and connected with each other so they let me know about my own progress."

4.3.2. Adaptation

Adaptation refers to data literacy actions in which the runners adapted their activities and interpretations of the data based on the recognized limitations of their tracking devices. One form of adaptation is the selective use of features. Runner 981 explained that they considered the digital measurements to be trustworthy overall but "only track the heart rate, the distance, and the variation of progress over time." In other words, based on the perception of her information needs, the runner opted to use only certain measures, even though there would be a wider variety of trusted affordances available. Runner 165 described a similar stance when she explained why she had opted not to monitor her recovery times. According to her, the estimated recovery time was based on the mean heart rate of the exercise, which she was unable to track accurately enough at the moment.

> The heart rate belt is missing, so I'm using a wrist heart rate measurement. I don't find the wrist heart rate measurement very reliable, so I don't put much weight on the numbers. The recovery estimate is largely based on the average heart rate (?) of the run, so I'm not really monitoring the recovery estimate before the next run, either.

Another example of adaptation was the strategic interpretation of the data. Runner 154 wrote, "VO2 max and other analyses are, in my mind, more about monitoring your own progress through changes, but I don't have much faith in the numbers themselves." In other words, she did not trust the exact measurements of VO2 max (the maximal aerobic capacity) but considered the measurement error to be static. Instead of the actual numbers, her focus was on the relative change in numbers, and the adaptation allowed her to compare the data from different runs to track the development.

4.3.3. Optimization

Optimization can be understood as a subset of adaptations. Recognition of the "blind spots" and shortcomings of sports technology led some runners to implement practices that—according to them—improved the accuracy, reliability, and comparability of the data. Runner 508 explained that they did "fitness tests etc. in a half serious manner, and when done more often, they give a reasonable indication of where I am." Put differently, the respondent conducted fitness tests on a regular basis to build a solid database to minimize the bias caused by (possible) errors in individual tests.

Other runners made choices between different technologies based on the need they had for the accuracy of the information. This theme was particularly evident regarding which tracking devices, chest strap monitors, or sports watches with integrated optical sensors the runners choose to use in different situations. Runner 498, for instance, wrote that he used "the chest strap in power workouts and in the forest," whereas wrist monitoring was reliable enough during slow(er) paced runs, such as recovery runs and mileage building. Here, the respondent explained that he optimized technology use based on the type of workout and the geographical context in which he was running. Common types of power workouts are interval training or strides. They both include short(er) and fast(er) bursts (i.e., 4 min in threshold pace[3]) the aim of which is a rapid increase of the heart rate at the desired level (in threshold pace training, this is around 80–90% of the maximum heart rate). Each fast interval or stride is followed by a recovery period during which the heart rate should descend to the endurance training level (60–70% of the maximum heart rate).

5. Discussion

The motive behind the present study was to further our understanding of contextualized everyday data literacies. To achieve this objective, we selected a specific context (recreational running), specific data technology (self-tracking devices), and specific viewpoint (accuracy of data and analyses) to construct a substantial theory of one form of contextual data literacy. The research question was: How does recreational runners' everyday data literacy appear in relation to the accuracy of measurements and analyses of self-tracking devices?

Through an abductive analysis, we identified the data literacy actions that runners engaged with when assessing the accuracy of data and analyses in relation to their subjective needs, objectives, and life situations. The first-order data literacy actions—comparison and evaluation—described how runners assessed and analyzed the accuracy of the data, and they took place mainly in the immediate context of running. The second-order data literacy actions—acceptance, adaptation, and optimization—were the result of the runners' reflections on what they sought from running, how they valued data, and their broader life situation.

Our findings possess similarities and differences with previous research. First, the runners' experiences with measurement errors (see Section 4.1.2). were in line with the tests done for consumer-level self-tracking technologies (e.g., Johansson et al., 2020; Pasadyn et al., 2019; Vorlíček et al., 2021). Similarly, the runners' views about which measurements were more reliable than the others (see Section 4.2) echo previous research findings that complexity decreases reliability (Evenson et al., 2015; Fuller et al., 2020). Second, although our approach to data was different than in many other studies (e.g., self-tracking data vs. personal online data/research data), the data literacy actions in which our respondents engaged still contained similarities with other conceptualizations and frameworks.

Evaluation and comparison share similarities with Pangrazio and Selwyn's (2019) concept of "data understandings," which focuses on recognizing how data is generated and processed. This idea also aligns with Ridsdale et al. (2015) assertion that evaluation is a crucial aspect of data literacy. Similarly, comparing data with embodied sensations and data from different devices resembles the utilization and synthesis of multiple data sources found in certain data literacy frameworks (e.g., Gummer & Mandinach, 2015; Prado & Marzal, 2013). While subjective and temporal bodily experiences are not considered "official" data, they play a significant role in runners' sense-making processes (Hockey, 2013). Hence, understanding people's relational and contextual data literacy in specific aspects of human life necessitates acknowledging these experiences. In fact, Clegg et al. (2020, pp. 23–24) even suggest that (experienced) athletes perceive sensory experiences as "felt data," which they coordinate with "sensor data and other quantitative metrics to validate and sometimes repudiate one form of data over the other—facilitating a more critical perspective of sensor-based and statistical data."

Optimization, in turn, corresponds with "data tactics," which asks how one can do data differently (Pangrazio & Selwyn, 2019). In our study, the tactical aspect of data primarily focused on optimizing data quality by selecting the most appropriate technology for specific purposes (e.g., training/recovery runs) and contexts (e.g., flat/hilly terrain). For instance, runners made informed decisions regarding the use of less accurate optical (wrist) or more accurate traditional (chest) heart rate monitors based on the intended purpose of their runs, effectively choosing "suitable sensors for gathering data" as described by Ghodoosi et al. (2023, p. 118). Optimization naturally requires an understanding of the factors that influence data quality, and the same principle applies to adaptation, which will be discussed below.

Adaptation, as a way to make use of the less-than-optimal data relates to the domain of "data use," which is about peoples' interpretative competencies regarding data (Pangrazio & Selwyn, 2019). Adaptation also bears resemblance to the concepts of problem identification with data and application of data, which are commonly found in data literacy frameworks (e.g., Ghodoosi et al., 2023; Gummer & Mandinach, 2015; Ridsdale et al., 2015). As a practical example, the runners did not consider the observed measurement errors to be excessively significant when planning their subsequent runs and evaluating their progress. Runner 154's decision to focus solely on the relative development of VO2Max values (as described in Section 4.3.2) serves as a particularly illustrative instance of the latter. While the runner lacked trust in the actual numerical values, through adaptation, they were able to make use of the relative change in measurements. However, the runners also noted that these same errors rendered recovery time estimations useless and necessitated selective utilization of features on their sports watches.

The main difference is that the "messy" realities of human life that were lively present in the data are something that abstract and decontextualized data literacy frameworks easily miss or neglect. Often, the image of a data literate citizen reminds of the unswervingly rational "homo economicus" (see Levitt & List, 2008) who, in the case of data literacy, is a flexible life-long learner (see Uusitalo, 2010) that aims to constant self-improvement with (i.e., using data as the basis of decision-making) and about data (i.e., critical data literacy) (e.g., Coşkun & Karahanoğlu, 2023; Jin et al., 2022; Swan, 2012; Wolff et al., 2016). The image of everyday data literacy in our data was quite different. Many of our respondents wrote that they did not need the data to be as accurate as possible, and that "close enough" was a sound level of accuracy for their purposes. However, the acceptance of the limits of self-tracking data was not about a lack of knowledge or "data illiteracy." Instead, it was an intentional and agentic choice (see also Vartiainen et al., 2022) based on the reflection of various factors.

The mundane nature of our respondents' data literacy actions highlights that the framework presented in Figure 2 is not normative. Even though it provides an in-depth account of peoples' meaning-making with self-tracking data, it does not provide information on the kind of data literacy actions people should engage with. We share Markham's (2020, p. 235) view that "despite the political pressure to find ways of standardizing [data] literacy education, we understand that the actual situations in which such literacy is prompted are highly contextual. A variety of actions and strategies could work equally well." Put differently, the finding that some runners optimize their data generation practices does not mean that all runners should follow their example or that optimization is a "virtue" to be practiced in all data-related situations, regardless of the context. Neither do we suggest that acceptance is a wise option to follow by default.

This "down to earth" approach locates our study within the growing body of literature exploring the "usually unnoticed and below the surface everyday routines, contingencies, and accomplishments that both shape and emerge through our engagements with digital data" (Pink et al., 2017, p. 1; see also Ciccone, 2022; Clegg et al., 2020; Lupton et al., 2018; Markham, 2020). Indeed, we wish that our study (and the ones cited above) encourages researchers to explore the contextual data practices, literacies, and agencies of diverse groups of people. We recognize several advantages of employing bottom-up approaches like the one utilized in our study. Firstly, in addition to generating contextual understanding, such studies can serve as an informed and context-sensitive foundation for the development of (more) comprehensive data literacy frameworks. Secondly, the utilization and development of context-sensitive concepts (such as conforming comparison, acceptance, and optimization in our case) can imbue the somewhat abstract notion of data literacy with more significance and accessibility for individuals from diverse backgrounds and interests (for a more in-depth discussion on contextual conceptualization, see Palsa & Mertala, 2019). We believe that employing context-sensitive and inclusive terminology can effectively engage individuals in observing and contemplating the role of data literacy within specific domains of their lives, such as recreational running. Subsequently, these observations and reflections can be compared with those from other domains, such as personal data and social media (see Pangrazio & Selwyn, 2019). This comparative analysis can lead to the realization of the need for more comprehensive data literacy concepts that can address the diverse range of contexts. This is where overarching frameworks, like the one proposed by Prado and Marzal (2013), become valuable conceptual tools for supporting public understanding of (big) data (Michael & Lupton, 2016).

By approaching everyday data literacy from the perspective of the accuracy of data and analyzing self-tracking devices, our study touched upon the questions around data production, assessment, and agency within certain boundaries. The contemporary digital environment of runners is highly convergent (Aliverti et al., 2022). Some runners share their runs via sport-related (i.e., Strava) and/or general (i.e., Facebook and Instagram) social media platforms (Carlén & Maivorsdotter, 2017; Littlejohns et al., 2019), and the accuracy of data may play a role in their sharing practices. To provide an (anecdotal) example, the second author of the present article hides his heart rate data from his public Strava profile due to constant measurement errors.[4] Second, the accuracy of hardware and software are outcomes of product development, in which the accumulative data from users play a notable role (e.g., Polar, 2022; Suunto, 2022). Although many runners do not agree to share their exercise data with third parties for commercial and other purposes without their consent (Wiesner et al., 2018), it is not known how people feel about sharing their data with the manufacturer (or are they even aware of the "share by default" policy). These questions are beyond the scope of the present article and are left for future research explorations.

Notes

1. In the field of Human–Computer Interaction research similar discussions are currently debated under the concepts of data sensemaking (Coşkun & Karahanoğlu, 2023) and data skills (de Boer et al., 2022).
2. There are indicative evidence that non-competitive "lone runners" use tracking technologies as well (Carlén & Maivorsdotter, 2017).
3. Anaerobic threshold refers commonly to an individual running pace which correlates the intensity at which lactic acid accumulates in the blood circulation faster than the body can clear it. In concrete terms Davis (1985) explains "the average marathon running speed has been shown to be closely related to the running speed at the anaerobic threshold."
4. The measurement error is known as cadence lock (see Figure 3). It is noteworthy that different applications offer contradictory evaluations of the author's performance based on this error. Polar Flow's Running Index compares pace with heart rate and concludes that the author is out of shape due to the high heart rate. On the other hand, Strava focuses solely on the heart rate and interprets it as a sign of intense training, predicting that the author is currently in peak physical condition. However, neither of these interpretations is accurate.

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Appendix: The questionnaire

Question	Type
Age	Numerical
Gender	Female, male, other, I wish not to specify
How many times a week do you run on average	Numerical
How many times a week do you do other physical activity?	Numerical
What does running mean to you? For example, you can tell us about your running history and/or the motivation that makes you go running.	Open
Do you use technology* for your running? In this context, running includes not only the actual running activity but also the use of technology before (e.g., planning a run) and after (e.g., looking at analyses)* equipment (e.g., sports watch, heart rate belt) apps and services (e.g., Strava, virtual coaching).	Yes/No
What technologies do you use for your running? What do you use them for, and why? Running, in this context, includes not only the actual running activity but also the use of pre-running (e.g., planning a training session) and post-running (e.g., viewing analyses) technologies.	Open
Are there features of the technologies you use that you do not use? What are they, and why do you not use them?	Open
How accurate and reliable do you consider the measurements and analyses of the technologies you use (e.g., distance, speed, heart rate, fitness tests and assessments, personalized training programs)? Please justify your views.	Open
Why do you not use technology in your running?	Open