Is it just a score? Understanding Training Load Management Practices Beyond Sports Tracking

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ABSTRACT

Training Load Management (TLM) is crucial for achieving optimal athletic performance and preventing chronic sports injuries. Current sports trackers provide runners with data to manage their training load. However, little is known about the extent and the way sports trackers are used for TLM. We conducted a survey (*N*=249) and interviews (*N*=24) with runners to understand sports tracker use in TLM practices. We found that runners possess some understanding of training load and generally trust their trackers to provide accurate training load-related data. Still, they hesitate to strictly follow trackers' suggestions in managing their training load, often relying on their intuitions and body signals to determine and adapt training plans. Our findings contribute to SportsHCI research by shedding light on how sports trackers are incorporated into TLM practices and providing implications for developing trackers that better support runners in managing their training load.

CCS CONCEPTS

• **Human-centered computing** → Empirical studies in HCI.

KEYWORDS

Training load management, SportsHCI, running, human-data interaction, sports tracking, personal informatics

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1 INTRODUCTION

Ongoing developments in mobile apps and smart watches have enabled runners to track various sports performance-related measures [61]. Sports tracking apps like *Run Keeper*[1] and *Map My Run*[2] provide insights into running performance, motivate runners to go for a run, and challenge them to beat their personal best times [74]. Accurate [76] and advanced [54] data becomes critical for many runners in pursuing their running-related goals. Most runners rely on metrics to monitor their performance [46]; some are *measured* metrics, such as distance and time of a workout, while others are *derived* metrics, such as VO_2Max, training frequency, or "suffer score". Tracking and presenting such metrics, sports trackers could help runners with Training Load Management (TLM).

Monitoring and managing the training load requires more knowledge and skill than checking performance metrics [31]. Specific knowledge about the underlying biomechanical and physiological principles of sports training is vital to make sense of the performance measures and maximise the adaptation of an athlete's body to the training load [41]. It might not be evident to runners that measures such as VO_2Max (i.e., the estimate of maximum oxygen intake during exercise) and step frequency depend on one's body characteristics [75]. Such data does not always help improve performance, especially when metrics are not in line with the runner's expectations (e.g., no improvement in VO_2Max despite regular training).

[1]https://runkeeper.com/ (Retrieved on 19 August 2023)
[2]https://www.mapmyrun.com (Retrieved on 19 August 2023)

这只是一个分数吗？理解训练负荷管理超越运动追踪的实践

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摘要

训练负荷管理（TLM）对于实现最佳运动表现和预防慢性运动损伤至关重要。

当前的运动追踪器为跑步者提供数据以管理其训练负荷。然而，关于运动追踪器在训练负荷管理实践中的使用程度和方式知之甚少。我们通过一项调查（N=249）和访谈（N=24）与跑步者交流，以了解运动追踪器在训练负荷管理实践中的使用情况。我们发现跑步者对训练负荷有一定理解，并普遍信任其追踪器提供的训练负荷相关数据的准确性。尽管如此，他们在严格遵循追踪器建议管理训练负荷时仍犹豫不决，

往往依赖直觉和身体信号来确定和调整训练计划。我们的发现通过揭示运动追踪器如何融入训练负荷管理实践，并为开发能更好支持跑步者管理训练负荷的追踪器提供启示，从而为体育人机交互研究做出贡献。

CCS概念

• **以人为本的计算 → 人机交互实证研究。**

关键词

训练负荷管理，体育人机交互，跑步，人数据交互，运动追踪，个人信息学

美国计算机协会参考文献格式：
阿尔马甘·卡拉汉奥卢、艾库特·科斯昆、迪斯·波斯特马、鲍克·伦纳德·谢尔廷加、鲁本·古维亚、丹尼斯·雷德斯马与贾斯珀·雷纳尔达。2024年。这只是一个分数吗？理解训练负荷管理实践超越运动追踪。收录于《计算机系统中的人为因素会议论文集》（*CHI 2024大会*），*2024年5月11日至16日*，美国夏威夷州檀香山。美国计算机协会，

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1 引言

移动应用程序和智能手表的持续发展使跑步者能够追踪各种与运动表现相关的指标[61]。诸如跑步助手1和我的跑步地图2等运动追踪应用程序不仅提供关于跑步表现的洞察，还能激励跑步者坚持跑步，并挑战他们突破个人最佳成绩[74]。

准确[76] 且先进[54] 的数据对许多追求跑步相关目标的跑步者至关重要。大多数跑步者依赖指标来监控他们的表现[46]；其中一些是测量指标，如锻炼的距离和时间，而另一些则是衍生指标，如最大摄氧量、训练频率或“痛苦指数”。通过追踪和呈现这些指标，运动追踪器可以帮助跑步者进行训练负荷管理（TLM）。

监测和管理训练负荷需要比检查表现指标[31]更多的知识和技能。了解运动训练背后的生物力学和生理学原理对于理解表现指标并最大化运动员的身体对训练负荷的适应[41]至关重要。跑步者可能并不清楚，诸如最大摄氧量（即运动时最大氧气摄入量的估计值）和步频等指标取决于个人的身体特征[75]。这类数据并不总能帮助提升表现，尤其是当指标与跑步者的预期不符时（例如，尽管定期训练但最大摄氧量没有提升）。

1https://runkeeper.com/（检索于2023年8月19日）
2https://www.mapmyrun.com（检索于2023年8月19日）

To effectively use sports trackers in managing training load, runners must transform the data into meaningful narratives and interpretations [23]. Data interpretation is an intricate task involving data collection and organisation, identification of patterns in data, and extraction of meaningful insights [80]. This process can be challenging for runners without sufficient sports training knowledge, potentially leading to inappropriate training load planning. As a general guideline, it is not recommended to increase the training load by more than 10% per week in terms of duration, intensity, or frequency to avoid overloading [70]. Increasing load by over 30% per week, especially for novice runners, raises the risk of running-related injuries [64]. Scenarios such as exceeding the body's capacity with excessively high weekly running distances or having excessive rest between running workouts [34] pose problems, as unsuitable training loads, whether too high or too low, can increase the risk of running-related injuries [1, 83].

Runners have different attitudes towards running performance, which affect how they interpret and interact with running related data. Sensemaking of such data may result in complying with, negotiating with, or ignoring it [17, 18]. These behaviours can vary across data types, with individuals tending to focus more on one favourite type of performance metric while intentionally overlooking unsatisfactory performance measures [17]. Snooks et al., [82] argue that fixating on specific metrics might cause more harm than benefit when people change their behaviour to fulfil sports trackers' expectations. In the long term, this approach may foster an unhealthy obsession with athletic performance and "being emotionally invested" in hitting the numbers [63] rather than a fundamental understanding of the underlying meaning of numbers.

Designing trackers to help runners monitor and understand data for better TLM practices requires sports science and SportsHCI knowledge. Previous work in sports science articulates the underlying dimensions of training load [e.g., 36], how to measure training load by utilising various external (e.g., distance) and internal training load metrics (e.g., heart rate) [e.g., 41], and argues for the role of mental factors [e.g., 22]. In HCI, studies showed the contribution of technology to measure physical metrics by employing wearables that quantify training load measures (e.g., biomechanical and physiological data) [68]. In addition, several studies presented guidelines on how to convey physical activity data to users in a clear [27], engaging [71] and appealing way [30].

Yet, runners have their way of assessing the accuracy of running related data that starts from data interpretation and goes beyond clear and engaging data representations [67]. Furthermore, the primary focus of current sports trackers is more on accurately representing individual metrics (e.g., VO_2Max) than how they relate to each other, which may hinder runners' ability to obtain actionable insights from their data. Finally, in HCI literature, little is known about how runners use running-related data for TLM, and what they track for managing their training loads and to what extent they comply with the TLM suggestions of trackers.

Recently, the work of Rapp and colleagues [72] provided insightful contributions to our understanding of the use of personal informatics (PI) in sports. They discovered that while amateur athletes (i.e., individuals who are highly trained but not competitive at national /international level) tend to trust the objectivity of the parameters monitored by their devices, elite athletes (i.e., individuals who currently compete at national and international level with national titles [85]) often rely more on their sensations. They also identified a significant gap in the use of PI tools among amateur athletes, arguing that these tools do not adequately guide them in understanding and interpreting their data. This finding is particularly relevant to our research. We argue that misinterpretations or misuses of training data can have significant negative consequences for runners, such as increased risk of injury, and better technology design could alleviate these problems [93]. Hence, TLM is not just a matter of optimizing performance in running but is also crucial for injury prevention in other sports, such as cycling [89], swimming [5], and team sports [59]. Understanding how runners manage their training load more profoundly could help design sports trackers to better guide TLM, and thus help avoid undesirable outcomes. Such an understanding is missing in existing SportsHCI studies.

In this paper, we address this gap through a survey and interview study answering the following questions: (1) How do runners use their sports data for TLM? and (2) how do they perceive and use sports trackers' TLM suggestions? We first explain TLM in sports and illustrate how TLM practices are supported in sports informatics. Then, we report the results of our studies to articulate runners' sports tracker use for TLM purposes. Our findings contribute to SportsHCI research by understanding runners' sports tracking practices in TLM. Through the survey and interviews with runners, we shed light on (1) how runners decide on and adapt their training program with data and guidance provided by sports technology and (2) how this data and guidance help them develop competency in TLM. This understanding allows us to identify implications for future tracking tools that support TLM, contributing towards better designs that address runners' TLM-related needs. We also give novel directions for sports science regarding identifying, presenting, and interpreting data, which will help runners get optimal benefits from their workouts (e.g., performance enhancement and sustained enjoyment).

Furthermore, we inform the development of smarter and personalised sports tracking that support athletes' performance and health, which can go beyond the running context. Such an understanding can lead to developing more integrated sports trackers for TLM and pave the way for more personalised use of sports technology across various sports. Therefore, this paper has the potential to inform not only the field of HCI and sports technology but also the broader domain of sports science and athlete health management.

2 RELATED WORK

2.1 Training Load Management in Sports

Training load is the workload that relates to physical training [10]. It can be either internal or external, where the former refers to the physiological response of the athlete to training, and the latter refers to the physical demands imposed on the athlete [41]. The internal load can be quantified, for example, in terms of the heart rate (HR), blood oxygenation rate, and lactate levels and the external load in terms of, for example, the intensity, duration, and frequency of workouts. Each workout stimulates long-term responses (e.g., increase in VO_2Max) and short-term physiological adaptations (e.g., Excess Post-exercise Oxygen Consumption, EPOC) [50]. Workload

为了有效利用运动追踪器管理训练负荷，
跑步者必须将数据转化为有意义的叙述和解读[23]。数据解读是一项复杂的任务，涉及数据收集与整理、模式识别以及提取有意义的见解[80]。对于缺乏足够运动训练知识的跑步者而言，这一过程可能颇具挑战性，并可能导致训练负荷规划不当。根据通用准则，建议每周训练负荷的增加幅度（以持续时间、

强度或频率衡量）不应超过10%，以避免超负荷[70]。若每周负荷增幅超过30%（特别是对新手跑者而言），会显著增加跑步相关伤害的风险[64]。诸如每周跑步距离超出身体承受能力，或跑步锻炼间隔期间过度休息[34] 等情况都会引发问题——因为无论训练负荷过高还是过低，都可能增加跑步相关伤害的发生概率[1, 83]。

跑步者对跑步表现持有不同态度，
这影响了他们如何解读和互动跑步相关
数据。对此类数据的意义建构可能导致顺从、
协商或忽视[17, 18]。这些行为可能
因数据类型而异，个体往往更倾向于关注
某一偏爱的表现指标类型，同时有意
忽视了不令人满意的表现测量[17]。斯努克斯等人
认为，过分关注特定指标可能导致更多
害处而非益处，当人们改变行为以满足
运动追踪器的期望时。长期来看，这种做法可能
助长对运动表现和"情感投入"于达成数字的
不健康痴迷[63]，而非
对数字背后基本含义的根本理解。

设计追踪器以帮助跑步者监测和理解数据，从而实现更好的训练负荷管理实践，需要运动科学和体育人机交互知识。先前在运动科学领域的工作阐明了训练负荷的基本维度[例如36], 如何通过利用各种外部（如距离）和内部训练负荷指标（如心率）来测量训练负荷[例如41], ，并论证了心理因素的作用[例如22]。在人机交互领域，研究表明技术通过采用量化训练负荷测量的可穿戴设备（如生物力学和生理数据）对测量身体指标的贡献[68]。此外，多项研究提出了如何以清晰的方式向用户传达身体活动数据的指南[27],

引人入胜[71] 且吸引人的方式[30]。
然而，跑步者有其评估跑步
相关数据准确性的方法，这始于数据解读并超越于此
清晰且引人入胜的数据表示[67]。此外，
当前运动追踪器的主要关注点更侧重于准确
呈现个体指标（如最大摄氧量），而非它们之间的
关联性，这可能阻碍跑步者从数据中获取可操作的
洞察。最后，在人机交互文献中，关于跑步者如何
利用跑步相关数据进行训练负荷管理（TLM）的方式及
他们追踪哪些数据来管理训练负荷以及
在多大程度上遵循追踪器提供的TLM建议。

最近，Rapp及其同事[72] 的研究为我们理解个人信息学(PI)在体育中的应用提供了深刻见解。他们发现，虽然业余运动员（即训练有素但未达到国家/国际水平竞赛级别的个体）倾向于信任其设备监测参数的客观性，

而精英运动员（即当前在国家及国际级别赛事中竞争并拥有国家级头衔[85]的个体）则更依赖自身感觉。他们还发现业余运动员在使用PI工具方面存在显著缺口，认为这些工具未能充分指导他们理解和解读数据。这一发现与我们的研究尤为相关。我们认为，对训练数据的误读或误用可能给跑步者带来重大负面后果，如受伤风险增加，而更好的技术设计可以缓解这些问题[93]。因此，训练负荷管理(TLM)不仅关乎优化跑步表现，对于自行车运动[89], 、游泳[5], 和团队运动[59]等其他运动的伤害预防也至关重要。更深入地理解跑步者如何管理训练负荷，有助于设计能更好指导TLM的运动追踪器，从而避免不良结果。现有体育人机交互研究中尚缺乏此类理解。

本文通过一项调查与访谈研究
填补这一空白，回答以下问题：(1) 跑步者如何利用
运动数据进行TLM？以及(2) 他们如何感知并运用
运动追踪器的TLM建议？我们首先阐释运动领域中的TLM概念
并阐述训练负荷管理实践如何在体育信息学中得到支持。随后，我们通过研究结果来阐明跑步者

为训练负荷管理目的使用运动追踪器的情况。我们的发现为
体育人机交互研究提供了关于跑步者在训练负荷管理中运动追踪实践的深入理解。通过对跑步者的调查与访谈，我们

揭示了（1）跑步者如何根据运动技术提供的数据与指导决定并调整其训练
计划，以及（2）这些数据与指导如何帮助他们发展
以及（2）这些数据和指导如何帮助他们发展能力
在跑者的训练负荷管理中。这一认知使我们能够明确
未来支持训练负荷管理的追踪工具的开发意义，从而推动更优质的
设计方案以满足跑者对训练负荷管理的需求。我们还为
运动科学领域提供了新方向，涉及数据的识别、呈现与解读，这将帮助跑者从锻炼中获取

最佳效益（例如性能提升与
持续享受）。

此外，我们宣布开发更智能、个性化的运动追踪技术，以支持运动员的表现和健康。

这可以超越跑步情境。这样的理解
可以推动开发更多用于训练负荷管理的集成运动追踪器
并为运动技术的更个性化使用铺平道路
跨越多种体育项目。因此，本文有可能
不仅为人机交互和运动技术领域提供信息，还
运动科学及运动员健康管理的广阔领域。

2 相关工作

2.1 运动中的训练负荷管理

训练负荷是与身体训练[10]相关的工作量。
它可以是内部的或外部的，前者指运动员对训练的生理反应，后者指施加于运动员的身体需求[41]。内部负荷可通过例如心率（HR）、血氧饱和度和乳酸水平来量化，而外部负荷则可通过例如锻炼的强度、持续时间和频率来衡量。每次锻炼都会激发长期反应（例如，

最大摄氧量的提升）和短期生理适应（例如，
运动后过量氧耗 (EPOC) [50]。工作量

is a highly dynamic, individual, and multidimensional construct that a single metric cannot capture.

It is comparatively easier to quantify external load than internal load. One way is to calculate the acute-chronic workload ratio (ACWR) [19, 42]. The acute phase is an athlete's most recent training load, and the chronic phase is the training load the athlete's body is used to and prepared for [33]. ACWR employs several performance measures, such as training intensity and volume (or amount) of training [32]. Some of these are easy to measure and track with current sports trackers. For example, training intensity can be differentiated by looking into a runner's metrics of jogging and sprinting. During running, runners' HR (i.e., internal load) varies as a reaction to factors such as running speed and duration (external load). Hence, HR data [50] across a workout [31, 48], combined with the duration of the exercise, become the input to calculate training intensity [25, 29]. However, athletes' subjective perception of the training intensity is also crucial for accurate internal training load measures, as in the rating of perceived effort (RPE) [5], which is a reliable and common way to quantify and assess internal load [17, 40]. Sports trackers can collect this input by asking how the athlete feels about the intensity of a past workout and calculate ACWR accordingly.

An essential aspect of the ACWR is the definition of a "sweet spot", a ratio between 0.8 and 1.3 (which can be up to 2.5), where the risk for a chronic injury is low and athletic performance can still be enhanced [42]. An athlete can gradually progress to high chronic workloads by consistently implementing training workloads within this sweet spot range. It can be assumed that continuously increasing the training intensity (e.g., running faster), frequency (e.g., running more often) or volume (e.g., running farther) can enhance performance. However, training physiology principles dictate proper resting time before the next training to avoid physiological overload and help recover muscle and tissue damage [69]. Without sufficient rest (i.e., the acute-chronic workload ratio is higher than 1.5), the athlete's body cannot recover from the previous training, increasing the risk of accumulation of tissue damage [7, 32, 69].

Another strategy to manage training load involves integrating the periodisation philosophy of sports training into training plans and providing more flexible micro (i.e. daily), meso (i.e. monthly) and macro (i.e., yearly/life-long) training cycles [8]. A comprehensive macro training cycle is subdivided into meso and micro cycles, where the intensity and the volume of the training sessions are defined based on the athletes' response to micro and meso training cycles. These data-based, personalised cycles can make the training plans fit the athletes' daily routines and effectively mitigate the possibility of overloading to sustain life-long activity [47].

Sports periodisation literature emphasises the significance of adequate recovery in preventing overuse injuries and overtraining syndrome [60, 83]. Monitoring training load emerges as a significant method to avoid such setbacks. Even though preventable with proper TLM [57, 68], overuse-related lower extremity injuries are common among runners [40, 65]. Around 37%–56% of runners have running related overuse injuries yearly [53, 91], and numbers still increase [92, 94]. These facts bring us to the importance of monitoring and managing training loads to avoid the overloading effects of training and mitigate the overuse-related injury risk factors [6, 39, 95]. We think that sports trackers can help in avoiding such overloading effects.

2.2 Training Load Monitoring Practices in Sports Informatics

The primary driving force behind sports technology development is enhancing metric accuracy for predicting human performance [86]. Consequently, current sports trackers offer athletes an immense amount of data [90]. These tools can collect, analyse and synthesise performance-specific data and give individualised feedback and recommendations [35, 56, 74] supporting TLM practices of runners [84], particularly for those who plan the details of their own training. One example is the Garmin sports trackers, which combine HR data with EPOC. By summing the athlete's oxygen consumption measurements over the past seven days and comparing them with the runners' four-week Chronic Training Load[3], these trackers calculate Acute Training Load. Subsequently, they provide the runners with a four-week training load focus (Figure 1a) and illustrate what range the athlete should be training. In the provided example (Figure 1a), it is evident that the runner is underloading the "anaerobic" training, and the tracker shows that the athlete is missing a particular type of training (Figure 1a, purple coloured) and overloading in another (Figure 1a, orange coloured). Within the app interface (Figure 1b), the tracker provides more comprehensive information regarding performance measures and training load and their impact on performance enhancement.

Another sports tracker series, Suunto, uses the Training Stress Score to quantify training load[4]. This score is based on the training impulse, which uses the intensity and duration of the workouts, together with HR data and the runner's pace, to calculate short-term and long-term training loads. The short-term training load is referred to as Acute Training Load and is a 7-day average of the training stress score, while the long-term load is referred to as Chronic Training Load (or fitness), a 42-day weighted average of the training stress score[5]. Running tracking apps, like Strava, Run Keeper, Adidas Running, Map My Run, and Train As One[6], provide limited information about training load to freemium users. In contrast, premium users can access more advanced features, like training plans, based on their training load measures. For example, Strava app (Figure 1c) provides a graphical representation of training load and signals how the relative effort of an athlete changes over time. Training and performance enhancement-focused platforms like Training Peaks[7] also provide advanced features (e.g., peak performance analysis), metrics (e.g., training stress score) and training customisation opportunities.

Although current sports trackers use training knowledge to calculate training load, they do not immediately provide actionable insights about how this information could be implemented for TLM.

[3]https://discover.garmin.com/en-US/performance-data/running/#training-load (Retrieved on 24 July 2023)
[4]https://www.suunto.com/sports/News-Articles-container-page/training-stress-score-in-suunto-app (Retrieved on 24 July 2023)
[5]https://www.suunto.com/sports/News-Articles-container-page/understand-and-manage-your-training-load-with-suunto (Retrieved on 24 July 2023)
[6]https://www.strava.com/features ; https://runkeeper.com ; https://www.runtastic.com ; https://www.mapmyrun.com ; https://www.trainasone.com
[7]https://www.trainingpeaks.com (Retrieved on 23 July 2023)

是一个高度动态、个体化且多维度的构念
单一指标无法全面捕捉。

量化外部负荷比内部负荷相对容易。一种方法是计算急性-慢性工作量比（ACWR）[19, 42]。急性阶段指运动员最近的训练负荷，而慢性阶段则是运动员的身体已适应并做好准备的训练负荷[33]。ACWR采用多种表现测量指标，如训练强度与训练量（或训练时长）[32]。其中部分指标通过现有运动追踪器即可轻松测量与追踪。例如，通过分析跑步者的慢跑与冲刺指标可区分训练强度。跑步时，跑步者的心率（即内部负荷）会因跑步速度与持续时间（外部负荷）等因素产生波动。因此，锻炼过程中的心率数据[50] [31, 48],

结合锻炼的持续时间，成为计算训练强度[25, 29]的输入。然而，运动员对训练强度的主观感知对于准确的内部训练负荷测量同样至关重要，如自觉用力评分（RPE）[5], ，这是一种可靠且常见的量化和评估内部负荷[17, 40]的方法。运动追踪器可以通过询问运动员对过去锻炼强度的感受来收集这一输入，并据此计算ACWR。

ACWR的一个关键方面是定义“最佳点”，即介于0.8至1.3之间（最高可达2.5）的比率，在此范围内慢性损伤风险较低且运动表现仍可提升[42]。运动员通过持续在此最佳点范围内实施训练负荷，可逐步适应高慢性工作量。可以假设，持续增加训练强度（例如跑得更快），

频率（如增加跑步次数）或训练量（如延长跑步距离）可提升表现。但训练生理学原则要求在下一次训练前预留充足休息时间，以避免生理性超负荷并促进肌肉和组织损伤恢复[69]。若休息不足（即急性-慢性负荷比高于1.5），运动员的身体无法从前次训练中恢复，会增加组织损伤累积风险[7, 32, 69]。

另一种管理训练负荷的策略是将运动训练的周期化训练理念融入训练计划，并提供更灵活的微周期（每日）、中周期（每月）和宏周期（年度/终身）训练循环[8]。完整的宏周期训练会被细分为中周期和微周期，

其中训练课程的强度与训练量根据运动员对微周期和中周期训练的反应来设定。这些基于数据的个性化周期能使训练计划适配运动员的日常作息，有效降低超负荷可能性，从而维持终身运动习惯[47]。

运动周期化文献强调了充分恢复在预防过度使用损伤和过度训练综合症中的重要性[60, 83]。监测训练负荷成为避免此类问题的关键方法。尽管通过恰当的训练负荷管理可以预防[57, 68], ，但下肢的过度使用损伤在跑步者中仍十分普遍[40, 65]。每年约有37%至56%的跑步者会遭遇跑步相关的过度使用损伤[53, 91], ，且这一数字仍在上升[92, 94]。这些事实凸显了监测和管理训练负荷以避免超负荷的重要性。

训练的效果并减轻与过度使用相关的受伤风险因素[6, 39, 95]。我们认为运动追踪器有助于避免此类超负荷效应。

2.2 体育信息学中的训练负荷监测实践

体育运动技术发展的主要驱动力是提升预测人类表现的度量准确性[86]。因此，当前的运动追踪器为运动员提供了海量数据[90]。这些工具能收集、分析和综合特定表现数据，并提供个性化反馈与建议[35, 56, 74]，支持跑步者的训练负荷管理实践[84], ，尤其适用于自主规划训练细节的人群。以佳明运动追踪器为例，其将心率数据与运动后过量氧耗相结合。通过汇总运动员过去七天的耗氧量测量值，并与跑者四周的慢性训练负荷3进行对比，这些追踪器计算出急性训练负荷。随后，它们为跑者提供四周的训练负荷重点（图1a），并标示运动员应达到的训练范围。在所示范例（图1a）中，明显可见该跑者对“无氧”训练处于低负荷状态，追踪器显示其缺失某类训练（图1a紫色标注）而对另一类训练超负荷（图1a橙色标注）。在应用界面内（图1b），追踪器还提供了更全面的表现测量与训练负荷信息，及其对性能提升的影响。

另一款运动追踪器系列产品颂拓(Suunto)采用训练压力分数(Training Stress Score)来量化训练负荷4。该分数基于训练冲动(TRIMP)，通过锻炼的强度与持续时间，

结合心率数据和跑步者步频，计算短期与长期训练负荷。短期训练负荷称为急性训练负荷(Acute Training Load)，是训练压力分数的7日平均值；而长期负荷称为慢性训练负荷(Chronic Training Load，即体能状态)，是训练压力分数的42日加权平均值5。诸如Strava等跑步追踪应用，

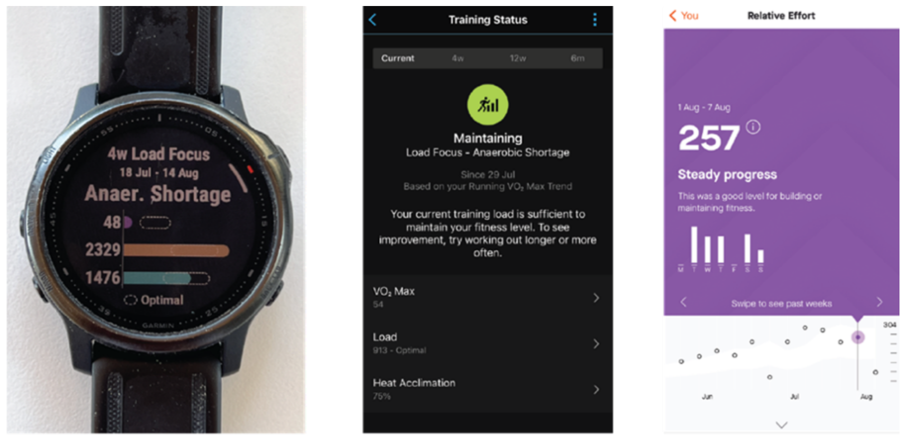
Run 6 Keeper、阿迪达斯跑步(Adidas Running)、我的跑步地图(Map M
仅向免费用户提供有限的训练负荷信息。
相比之下，高级用户可获取基于其训练负荷测量的更高级功能，例如训练计划。举例来说，

Strava应用程序(图1c)会以图表形式展示训练负荷，并显示运动员的相对努力如何随时间变化。专注于训练与表现提升的平台如Training Peaks7同样提供高级功能(例如，

峰值表现分析）、指标（如训练压力分数）以及训练定制机会。

尽管当前的运动追踪器利用训练知识来计算训练负荷，但它们并未即时提供关于如何将这些信息应用于训练负荷管理的可操作的见解。

3https://discover.garmin.com/en-US/performance-data/running/#training-load（2023年7月24日检索）
4https://www.suunto.com/sports/News-Articles-container-page/training-stress-score-in-suunto-app（2023年7月24日检索）
5https://www.suunto.com/sports/News-Articles-container-page/understand-and-manage-your-training-load-with-suunto（2023年7月24日检索）
6https://www.strava.com/features；https://runkeeper.com；https://www.runtastic.com；https://www.mapmyrun.com；
https://www.trainasone.com7https://www.trainingpeaks.com（2023年7月23日检索）



(a) Garmin sports watch interface (b) Garmin app interface (c) Strava app interface

Figure 1: Example Training Load Information from Garmin and Strava

Furthermore, interpreting training load measurements is complex due to the advanced sports training knowledge [11]. It requires significant effort to reflect on and act upon [46, 86]. Tracker data must be distilled with sports science knowledge to arrive at interpretations about performance and injury proneness [88].

Previous HCI work focused on understanding runners' practices of reflection-on-training through interactive systems. For example, an interactive mirror was employed in a recent study to translate complex training data into qualitative interfaces and understand the negotiation styles runners prefer to achieve life-training balance [77]. Still, HCI researchers should be aware that even though runners know the risks of training overload [55], the majority believe that they already know the limits of their bodies, and they tend not to limit excessive training [81], which can be detrimental due to the reasons explained above. Thus, informing the design of sports trackers, which can successfully guide runners in determining the *sweet spot* for training load, becomes a relevant goal for SportsHCI research.

The importance of TLM stems from its role in balancing athletes' training efforts and recovery time and predicting sports performance and risk of overuse (or overloading) related sports injuries [24, 32, 83]. In addition, it can help prescribe individualised training plans and revise and adjust training schedules that can boost athletes' well-being [48]. Although professional athletes' TLM is done under the supervision of coaches, amateur athletes may not be able to work with a coach, resulting in less supported and informed self-coaching and understanding of sports data [72]. As we stated earlier, TLM requires competency and knowledge. Having sports trackers that support and empower runners is vital to managing the training load effectively. In that regard, we first need to understand runners' current TLM practices, how they track and interpret data from their runs, especially for TLM purposes, and to what extent they follow TLM-related suggestions from trackers. Such an inquiry follows up on the findings around the use of personal informatics in sports [54, 72] and data in running [46, 67]. It opens new research directions in SportsHCI, contributing to the design of sports informatics, specifically for performance enhancement and injury prevention.

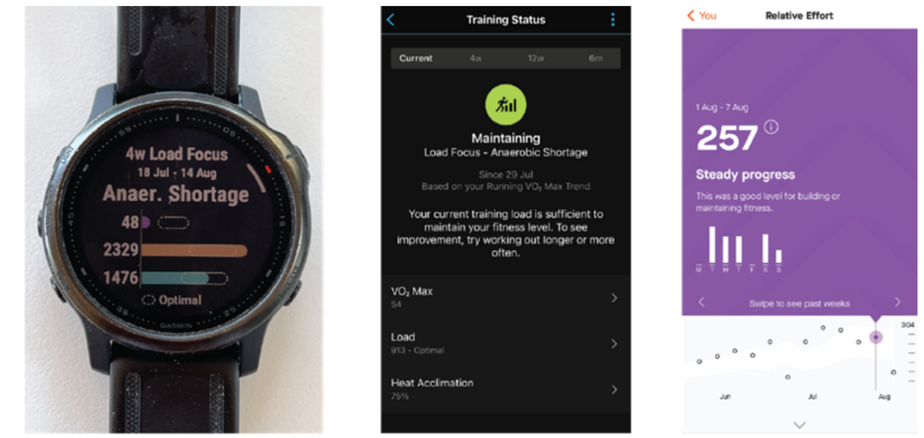
3 METHODS

We carried out an online survey followed by in-depth interviews to address (1) how runners use sports trackers when managing their training load (TLM) and (2) how they incorporate TLM-related tracker recommendations and performance predictions into their training. The survey gave us insights into why runners track their runs, particularly trackers' roles in managing training load. However, even after the survey, certain aspects remained unclear, such as specific ways runners integrate trackers into their TLM practices and how they make sense of and act upon TLM-related suggestions provided by trackers. Interviews helped us clarify these aspects and gain in-depth insights into technology-supported TLM practices. We obtained ethical approval from our research institute before participant recruitment.

3.1 Survey Study

Our survey questions drew on literature from HCI [37, 43, 44, 96] and sports science studies [e.g., 31, 36, 41, 49, 72, 74]. All authors, with a background in interaction design, HCI and sports science, reviewed the questions multiple times to arrive at the final form of the survey by checking their appropriateness for addressing the research questions. The survey asked participants their (1) demographics and running history; (2) tracking habits and tracking history; (3) motivations for tracking their runs [adapted from 37]; (4) sources they get help from while setting their running workouts (e.g., coach, technology or experiences runners); (5) reasons for changes in training routines; (6) metrics used to assess training load; and (7) trust in technology within the context of TLM (see Table 1).

Our questions included a combination of open-ended (e.g., age, years of experience in running), single-choice (e.g., running frequency per week) and five-point Likert and rating scale questions (e.g., importance of running metrics for TLM rates on a scale of 1=



(a) Garmin sports watch interface (b) Garmin app interface (c) Strava app interface

图1：佳明和Strava提供的训练负荷信息示例

此外，由于需要运用先进的运动训练知识[11]，解读训练负荷测量十分复杂。这需要投入大量精力进行反思并采取行动[46, 86]。必须结合运动科学知识对追踪器数据进行提炼，才能得出关于表现和受伤倾向的解读[88]。

先前的人机交互研究主要关注理解跑步者的训练实践
如何通过交互系统进行训练反思。例如，
最近一项研究采用了交互镜来转化
将复杂的训练数据转化为定性界面并理解
跑步者偏好的协商风格以实现生活与训练平衡
[77]。尽管如此，人机交互研究者应当意识到，即便跑步者知晓训练过度的风险[55], 大多数人仍认为

他们已了解自身身体的极限，且往往不会
限制过度训练[81], 这可能因上述原因
造成危害。因此，为运动设计提供信息
追踪器，能够成功引导跑步者确定
训练负荷的最佳点，成为体育人机交互的相关目标
研究
训练负荷管理（TLM）的重要性源于其在平衡运动员外在动机（EM）与内在动机（IM）中的关键作用。

训练负荷与恢复时间，并预测运动表现及过度使用（或超负荷）相关运动损伤的风险[24, 32, 83]。此外，它还能帮助制定个性化的训练计划，修订和调整训练日程，从而提升运动员的健康状况[48]。尽管职业运动员的训练负荷管理在教练监督下进行，但业余运动员可能无法获得教练指导，导致自我指导和对运动数据的理解缺乏支持与专业性[72]。如前所述，训练负荷管理需要能力与知识。配备能支持并赋能跑步者的运动追踪器，对有效管理训练负荷至关重要。就此而言，我们首先需要了解跑步者当前的训练负荷管理实践，他们如何跟踪和解读跑步数据（尤其是针对训练负荷管理目的），以及他们在多大程度上遵循追踪器提供的训练负荷管理相关建议。此类调查延续了关于体育中个人信息学应用[54, 72] 和跑步数据[46, 67]的研究发现，为体育人机交互领域开辟了新研究方向，有助于

体育信息学的设计，特别是针对性能提升与
伤害预防。

3 种方法

我们开展了一项在线调查，随后进行了深度访谈。
地址（1）跑步者如何在使用运动追踪器时管理他们的
训练负荷（TLM）与（2）他们如何整合与训练负荷管理相关的
追踪器的建议和表现预测融入他们的
训练。该调查让我们洞察了跑步者追踪其
跑步，尤其是追踪器在管理训练负荷中的作用。然而，即便在调查之后，某些方面仍不明确，例如

作为跑步者将追踪器整合到其训练负荷管理实践中的具体方式
以及他们如何理解并执行与训练负荷管理相关的建议
这些建议由追踪器提供。访谈帮助我们厘清了这些方面
并深入洞察技术支持的训练负荷管理实践。
在参与者招募前，我们已获得所属研究所的伦理批准
参与者招募。

3.1 调查研究

我们的调查问题参考了人机交互[37, 43, 44, 96]和运动科学研究[的文献，例如
31, 36, 41, 49, 72, 74]。所有作者，

均具备交互设计、人机交互和运动科学的背景，
通过多次审阅问题以确保其适当性能够解答研究问题，最终确定了调查表的形式。调查内容包括参与者：(1) 人口统计资料和跑步历史；(2) 追踪习惯和追踪历史；(3) 追踪跑步的动机[改编自37]；(4) 制定跑步训练时寻求帮助的来源（如教练、技术或经验丰富的跑者）；(5) 训练计划变更原因；(6) 用于评估训练负荷的指标；(7) 在训练负荷管理背景下对技术的信任（见表1）。

我们的问题包含开放式（如年龄、
跑步经验年限）、单选题（如每周跑步频率）以及五点李克特量表
和评分量表问题（如跑步指标对TLM的重要性评分，范围为1=

Table 1: Questions of the Online Survey

Item	Question	Type	Way of Data Collection
1-2	Age, running and tracking experience, weekly running volume	Open-ended (text box)	Numeric
1	Gender	Closed (single choice)	2 choices (female/male)
1	Running frequency	Closed (single choice)	7 choices (from 1-7 days)
1	Running injury history, training with a trainer	Closed (single choice)	Yes/No
2	Trackers being used	Open-ended (text box)	Text (brand of the sports watch)
2	Self-evaluation of running and TLM experience	Likert Scale (agreement)	2 items (i.e., I am experienced in running/managing my training load)
3	Motivation in tracking	Likert Scale (agreement)	10 items as delineated in [37]
4	Runners' sources of running workouts	Likert Scale (frequency)	6 questions about the way runners plan their running workouts
5	Reasons for changes in training routines	Likert Scale (agreement)	6 questions about the role of trackers in changing routines
6	Metrics to assess training load	Rating Scale (importance)	9 running-related data types that are important for TLM
7	Trust in Technology in TLM	Likert Scale (agreement)	3 questions (training metrics, training load, recovery time)

not at all to 5=very important). We ended the survey by asking respondents to leave their email addresses for follow-up interviews.

3.2 Interview Study

The semi-structured interviews consisted of three sets of questions built upon our survey questions. The first set of questions delved into runners' present motivations for tracking their runs (as was also asked in the survey; see Table 1, Item 3), including their uses and practices with their currently used sports trackers (following up on the survey questions listed Table 1, Item 2). The second set focused on the types of data used in running and TLM (Table 1, Item 6). Lastly, the third set of questions investigated the role of technology (e.g., smartwatches, apps, or other mediums) in runners' TLM and why they trust technology in TLM (Table 1, Item 4). This set also probed participants' trust in trackers' running-related calculations (e.g., VO_2Max calculations) and predictions (e.g., recovery time), commonly used to signal runners' training load (Table 1, Item 7). In short, interview questions were complementary to the survey questions. For example, in the survey, we asked participants why they changed their running routines, and in the interviews, we expanded on why and how these changes occur.

3.3 Participant Recruitment

Our data collection occurred over 4.5 months, between 1 March and 15 July 2023. We aimed to recruit runners with various running, tracking and TLM experience levels. To be included in our study, participants had to run at least twice a week over the last six months and monitor their running workouts with a smartwatch. We shared the online survey link via social platforms of a local marathon event, local running clubs, personal contacts and other social networks like Strava and Instagram. Our survey went online on the JotForm platform and was closed once no responses were received for five consecutive days. In total, we received 263 replies, of which we removed 14 due to respondents' lack of running experience (*N*=2), double entries (*N*=2), and not using a sports watch for tracking runs (*N*=10). The final number of responses was 249 (Table 2).

Survey respondents consisted of 34% (*N*=85) female and 66% (*N*=164) male runners, with an average age of 42.25 (*SD*=11.86). They were running for 10.89 years (*SD*=8.79), on average 3.26 days a week (*SD*=1.11), and 37.44 kilometres per week (*SD*=20.88). Of the respondents, 91% (*N*=227) were not injured by the time of the survey, but most (*N*=181, 73%) had some type of running related injuries before. These distributions are compatible with earlier large-scale running related studies [e.g., 21, 44]. On average, participants tracked their runs for 6.52 years (*SD*=4.70). The majority used a Garmin sports watch (*N*=179, 72%), followed by Apple (*N*=26, 10%) and Polar (*N*=26, 10%) to track their runs. About half (*N*=104, 42%) were following a plan from a running coach, while 145 (58%) did not follow a training plan from a running coach. Most runners thought they were above average experienced in running (*M*=3.69, *SD*=1.01) and in control of their training load (*M*=3.55, *SD*=0.96).

We reached out to runners again for the interview study. We informed them that the interviews would be recorded and conducted in English, and the recordings would be deleted after interview transcription. Of the 112 participants who received an email invitation for the interviews, 28 responded positively. Ultimately, we scheduled an interview with 24 runners who all submitted the survey (Table 3). Two authors interviewed each participant through the online video conferencing platform Microsoft Teams. All sessions were recorded. Prior to the recording, participants gave consent for the interviews to be recorded. The interviews took, on average, 45 minutes.

Interview participants comprised 9 female (38%) and 15 male (62%) runners, a ratio similar to our initial sample in the survey. They had on average 41.25 years of age (*SD*=11.83, Min =20, Max=70), were running for 12.17 years (*SD*=9.96, Min=2.5

表1：在线调查问题

Item	问题	Type	数据收集方式
1-2	年龄、跑步及追踪经验 每周跑步量	开放式（文本框）	数值型
1	性别	封闭式（单选）	2个选项（女性/男性）
1	跑步频率	封闭式（单选）	7个选项（从1到7天）
1	跑步受伤历史，训练时 trainer	封闭式（单选）	是/否
2	使用的追踪器	开放式（文本框）	文本（运动手表品牌）
2	跑步与TLM的自我评估 经验	李克特量表（同意度）	2个项目（例如，我在 跑步/管理我的训练负荷方面有经验）
3	追踪动机	李克特量表（同意度）	10个项目如[37]所述
4	跑者跑步训练来源	李克特量表（频率）	6个关于跑步者如何规划跑步训练的问题
5	训练计划变更原因	李克特量表（同意度）	6个关于追踪器在改变训练计划中作用的问题
6	评估训练负荷的指标	评分量表（重要性）	对TLM重要的9种跑步相关数据类型
7	对TLM技术的信任	李克特量表（同意度）	3个问题（训练指标、训练负荷、恢复时间）

完全不重要到5=非常重要）。我们在调查结束时请受访者留下电子邮件地址以便进行后续访谈。

3.2 访谈研究

半结构化访谈包含三组基于我们调查问题构建的问题。第一组问题深入探讨跑者当前追踪跑步的动机（调查中同样询问过；见表1，项目3），包括他们目前使用的运动追踪器的用途和实践（跟进表1项目2所列调查问题）。第二组问题聚焦于跑步和训练负荷管理中使用的数据类型（表1，

项目6）。最后，第三组问题探究了技术（如智能手表、应用程序或其他媒介）在跑者

训练负荷管理中的作用以及他们为何信任技术进行训练负荷管理（表1，项目4）。该组问题还探讨了参与者对追踪器跑步相关计算（如最大摄氧量计算）和预测（如恢复时间）的信任度，这些通常用于指示跑者的训练负荷（表1，

项目7）。简而言之，访谈问题是对调查问题的补充。例如，在调查中，我们询问参与者为何改变他们的跑步习惯，而在访谈中，

我们进一步探讨了这些变化发生的原因和方式。

3.3 参与者招募

我们的数据收集历时4.5个月，从3月1日至2023年7月15日。我们的目标是招募具有不同跑步、

追踪和TLM经验水平的跑步者。要纳入我们的研究，参与者需在过去六个月内每周至少跑步两次，并使用智能手表监测他们的跑步训练。我们通过本地马拉松赛事的社交平台分享了在线调查链接，

本地跑步俱乐部、个人联系人以及Strava和Instagram等其他社交网络。我们的调查在JotForm平台上线，并在连续五天未收到回复后关闭。总计收到263份回复，其中

因受访者缺乏跑步体验（N=2）而移除了14份，重复条目（N=2），以及未使用运动手表追踪跑步（N=10）。最终回复数量为249份（表2）。

调查受访者中女性跑者占34%（N=85），男性跑者占66%（N=164），平均年龄为42.25岁（标准差=11.86）。

他们平均跑步年限为10.89年（标准差=8.79），每周跑步3.26天（标准差=1.11），每周跑量为37.44公里（标准差=20.88）。91%的受访者（N=227）在调查时未受伤，

但多数人（N=181，73%）曾有过某种类型的跑步相关伤害。这些分布与早期大规模跑步相关研究[（例如21，44]）一致。参与者平均追踪跑步时长为6.52年（标准差=4.70）。大多数人使用佳明运动手表（N=179，72%），其次是Apple（N=26，10%）和Polar（N=26，10%）来追踪跑步。约半数人（N=104，42%）遵循跑步教练的训练计划，而145人（58%）未遵循跑步教练的训练计划。大多数跑者认为自己的跑步经验高于平均水平（平均值=3.69，

标准差=1.01）且能自主控制训练负荷（平均值=3.55，标准差=0.96）。

我们再次联系跑步者参与访谈研究，告知他们访谈将以英语进行并全程录制，录音将在文字转录后删除。在收到电子邮件邀请的112名参与者中，28人给予积极回应。最终我们与24名提交过调查的跑步者安排了访谈（表3）。两位作者通过在线视频会议平台Microsoft Teams对每位参与者进行访谈，所有会话均被录制。在录音开始前，参与者签署了访谈录制同意书。访谈平均耗时

45分钟。

访谈参与者包括9名女性（38%）和15名男性（62%）跑步者，该比例与我们调查初始样本相近。他们的平均年龄为41.25岁（标准差=11.83，最小值

=20, 最大值=70), 跑步了12.17年 (标准差=9.96, 最小值=2.5

Table 2: Demographics of the Survey Participants

	M	SD	Min	Max
Age	42.25	11.86	18	70
Running experience (in years)	10.89	8.79	0.5	50
Tracking experience (in years)	6.52	4.70	0.25	35
Running frequency (in days/per week)	3.26	1.11	1	7
Weekly running volume (in kilometres)	37.44	20.88	5	140
Experience in running (rating scale)	3.69	1.01	1	5
Confidence in controlling training load (rating scale)	3.55	0.96	1	5

Table 3: Characteristics of the Interview Study Participants

	Demographics			Experience (in years)		Running Frequency(in days)	Total weekly distance(in km)
	Age	Gender	Watch brand	Running	Tracking		
P01	41	Male	Garmin	4	4	4	50
P02	38	Male	Garmin	19	3	1	10
P03	46	Male	Garmin	10	10	5	60
P04	48	Male	Garmin	5	4.5	7	140
P05	39	Male	Garmin	7.5	7	5	78
P06	40	Male	Garmin	24	6	3	40
P07	32	Male	Garmin	4	4	3	25
P08	41	Male	Garmin	8	6	2	20
P09	44	Male	Garmin	6	6	4	40
P10	70	Female	Coros	45	8	5	40
P11	48	Female	Garmin	7	7	4	35
P12	58	Male	Polar	15	12	2	20
P13	56	Female	Garmin	25	14	3	25
P14	52	Male	Garmin	8	7	2	12
P15	32	Female	Garmin	12	10	2	20
P16	32	Female	Garmin	2.5	2.5	3	35
P17	48	Male	Polar	7	7	4	55
P18	20	Female	Apple	5	4	5	60
P19	21	Female	Garmin	15	10	2	30
P20	41	Male	Garmin	13	6	3	40
P21	37	Male	Garmin	4	4	6	120
P22	48	Female	Garmin	12	4	5	45
P23	35	Male	Polar	28	20	6	100
P24	22	Female	Garmin	6	3.5	2	10
AVR	42.15			12.17	7.27	3.67	46.25

years, Max=45 years), tracking their runs for 7.27 years (*SD*=4.11, Min=2.5 years, Max=20 years) and running 3.67 days a week recently (*SD*=1.58, Min =1 day, Max=every day). They had been running 47.83 kilometres weekly (*SD*=33.65 km, Min =10, Max=140). Most owned a Garmin watch (*N*=19), while the rest had either a Polar (*N*=3), Coros (*N*=1) or an Apple Watch (*N*=1). None of the respondents were injured by the time of the interviews, while 16 (67%) indicated they had running-related injuries in the past.

3.4 Data Analysis

We employed different analysis methods as the study yielded quantitative and qualitative data. Using IBM SPSS Statistics 26, we calculated means (*M*) and standard deviations (*SD*) for the survey questions with rating and Likert scales and frequencies for the open-ended questions like age, weekly running volume, and type of tracker used. We use these results to report the demographics of the participants.

For the interviews, we conducted qualitative data analysis [2, 62], following the same Reflexive Thematic Analysis (RTA) procedure proposed by [12, 15]. RTA was conducted by the first author, who conducted most of the interviews, and the second author, who was not involved in the interviews. These authors first downloaded the recordings and auto transcriptions provided by Microsoft Teams and reviewed the transcriptions with the recordings to ensure that the interviews were transcribed verbatim. Then, they read the transcripts while taking notes to familiarise themselves with the

表2：调查参与者人口统计

	M	SD	Min	Max
Age	42.25	11.86	18	70
跑步经验（年）	10.89	8.79	0.5	50
追踪经验（年）	6.52	4.70	0.25	35
跑步频率（天/周）	3.26	1.11	1	7
每周跑步量（公里）	37.44	20.88	5	140
跑步经验（评分量表）	3.69	1.01	1	5
控制训练负荷的信心（评分量表）	3.55	0.96	1	5

表3：访谈研究参与者的特征

	人口统计资料			经验（年）		跑步频率（天）	每周总距离(公里)
	Age	性别	手表品牌	跑步	追踪		
P01	41	Male	佳明	4	4	4	50
P02	38	Male	佳明	19	3	1	10
P03	46	Male	佳明	10	10	5	60
P04	48	Male	佳明	5	4.5	7	140
P05	39	Male	佳明	7.5	7	5	78
P06	40	Male	佳明	24	6	3	40
P07	32	Male	佳明	4	4	3	25
P08	41	Male	佳明	8	6	2	20
P09	44	Male	佳明	6	6	4	40
P10	70	女性	高驰	45	8	5	40
P11	48	女性	佳明	7	7	4	35
P12	58	Male	Polar	15	12	2	20
P13	56	女性	佳明	25	14	3	25
P14	52	Male	佳明	8	7	2	12
P15	32	女性	佳明	12	10	2	20
P16	32	女性	佳明	2.5	2.5	3	35
P17	48	Male	Polar	7	7	4	55
P18	20	女性	Apple	5	4	5	60
P19	21	女性	佳明	15	10	2	30
P20	41	Male	佳明	13	6	3	40
P21	37	Male	佳明	4	4	6	120
P22	48	女性	佳明	12	4	5	45
P23	35	Male	Polar	28	20	6	100
P24	22	女性	佳明	6	3.5	2	10
AVR	42.15			12.17	7.27	3.67	46.25

年, 最大值=45 年), 追踪他们的跑步记录7.27年 (标准差=4.11, 最小=2.5年，最大=20 年），近期每周跑步3.67天（标准差=1.58，最小=1 天，最大=每天）。他们每周跑步量为47.83公里（标准差=33.65公里，最小=10，最大=140）。

大多数人拥有佳明手表（N=19），其余人则使用Polar（N=3）、高驰（N=1）或苹果手表（N=1）。受访者在访谈时均未受伤，但有16人（67%）表示过去曾遭遇跑步相关伤害。

3.4 数据分析

我们采用了不同的分析方法，因为该研究产生了定量和定性数据。使用IBM SPSS统计软件26版，我们计算了调查问题中评分和李克特量表的平均值 (M) 和标准差 (SD)

以及频率数据。
开放式问题如年龄、每周跑步量及使用的追踪器类型
。我们利用这些结果来报告
参与者的人口统计资料。

对于访谈，我们进行了定性数据分析[2, 62]，遵循相同的反思性主题分析 (RTA) 流程由[12, 15]提出。RTA 由第一作者执行，他进行了大部分访谈，以及未参与访谈的第二作者。这些作者首先下载了由 Microsoft Teams 提供的录音和自动转录文本并对照录音审阅转录文本以确保访谈内容被逐字转录。随后，他们阅读了文字记录同时做笔记以熟悉

data (*Familiarization*). Next, the second author labelled the data from the first 12 interviews using inductive and deductive coding approaches (*Coding*). During deductive coding, survey questions were utilised as a reference (e.g., metrics to track while running or motivation to track running-related metrics). The data also induced codes, such as 'relying on feelings to judge training load". This coding was followed by reorganising the codes around initial themes, which were later synthesised into a preliminary codebook (*Generating initial themes*). Some example themes from this stage were "compliance with the training related suggestions", "perceived usefulness of data", and "feeling-driven training". The first and second authors come to a common understanding of the themes through a series of discussion sessions (*Developing and reviewing themes*). The first author coded the rest of the transcripts by using the revised codebook and initial themes as references and checked them against the data. All authors communicated frequently during this process to refine and finalise the themes (*Refining, defining and naming themes*). Once we had the final set of themes, we integrated them into a narrative coherent with our research questions (*Writing up*).

Accordingly, we present the results under four headings: motivation to track running, assessing training load, and sources of determining and changing training load to answer the first research question (*How do runners use their sports data for TLM*?), and trust in trackers in TLM to answer the second research question (*How do they perceive and use trackers' TLM suggestions*?).

3.5 Limitations

Our interview sample was predominantly male and Western, with 15 of 24 male participants. A similar gender distribution was observed in survey results (N=85 female and N=164 male runners). Besides, while we did not collect the country of residence from survey participants, we expect a bias given that the recruitment primarily focused on a local marathon event within Europe, local running clubs and personal contacts from the authors. Future research could explore how TLM practices vary in other cultures and a more equally distributed sample in terms of sex. For example, a study by Niess et al. [66] comparing fitness tracking practices across demographics suggests that Arab users prioritise physiological measurements over goals. This preference may impact the value of metrics and TLM suggestions provided by trackers for this group.

Further, our sample reported that their average experience in running ranges from 6 months to 50 years. The runners' experience levels might influence how they approach TLM and sports data. Literature suggests that more experienced runners are likely to underestimate their skills (and the opposite for less experienced runners: they tend to overestimate their skills, see [51, 52]). However, within the scope of this paper, we used this information for description purposes rather than comparing how runners with different "perceived running experiences" manage their training load. Future research could examine whether novice and experienced runners manage their training load with sports trackers differently.

4 USE OF TRACKERS IN TRAINING LOAD PRACTICES

In this section, we discuss the insights our studies yielded into runners' TLM knowledge and practices, their use of trackers for monitoring and managing their training load (RQ1) and their perception of trackers' TLM-related suggestions (RQ2). In general, we did not observe any instances where interview participants contradicted or disagreed with what was identified in the survey study. Yet, our interview results provided a more nuanced perspective on integrating trackers into runners' TLM practices. We will report the findings from the survey as well as the interviews based on the order of questions provided in Table 1.

4.1 Motivations for Running Tracking

Survey results showed that runners are interested in "*learning how they can improve themselves*" (M=4.22, SD=0.81). Tracking their runs "*gives pleasure to learn about themselves*" (M=4.16, SD=0.85) and is "*a good way to improve performance*" (M=4.10, SD=0.86). They "*feel better when they track their runs*" (M=3.96, SD=0.93) and find it a good way to "*develop themselves*" (M=3.96, SD=0.96). These results demonstrated that participants in our survey are intrinsically motivated to track their runs (see Table 4 for all the survey items). Tracking runs for "*preventing running related injuries*" was rarely the focus for tracking (M=2.32, SD=1.23).

The interview results support these survey findings. A large majority of the interviewees (N=19) indicated using trackers to see their progress towards a target running race (e.g., running a half marathon), and assess performance improvements through self-comparisons (e.g., comparing one's performance with six months and one month before the race). The most salient perceived benefit of tracking runs is that various running-related metrics allow runners to assess their performance (N=13). For example, P21 illustrated this as:

> *"I think it is good to have an overview. And in running, it quickly became a means to plan. If you plan stuff, you also want to record what you do and see if your realisation is the same as planning. It is **very valuable to look back and see patterns, whether they lead to an injury or your performance progresses**. Then, you try to relate what you are doing to whether you progress or not and whether you get injured or not. So, I think those are the most important reasons. Getting a watch that **records everything was a thing of convenience**. I wanted to **have instant data during the run**. A watch was the obvious way to get started."* (P21, M).

The second prominent motivation for tracking runs is to learn about running behaviour (N=14). On the one hand, runners are curious about their performance metrics and what the technology can bring them (N=5). On the other hand, they believe that trackers record their running more accurately than their memory, thus supporting better learning (N=11). Furthermore, according to our participants, using trackers is not only about assessing performance based on metrics but also about learning how to be a "better runner". For instance, almost half of the participants mentioned that data provided by the trackers helped them better understand the

数据（熟悉阶段）。接着，第二作者对数据进行了标注来自前12次访谈，采用归纳与演绎编码方法（编码）。在演绎编码过程中，调查问题被用作参考（例如，跑步时追踪的指标或追踪跑步相关指标的动机）。数据还诱导出的编码，如‘依赖感觉判断训练负荷’。随后围绕初始主题对这些编码进行了重组，这些主题随后被综合成初步的编码手册（生成初始主题）。此阶段的一些示例主题包括“对训练相关建议的遵从性”、“感知数据的有用性”以及“感觉驱动的训练”。前两者第二作者就主题达成共识通过一系列讨论会（开发和审查主题）。第一作者使用修订后的编码手册和初始主题作为参考，对剩余文字记录进行编码并对照数据进行检查。所有作者在此过程中频繁沟通，以完善并最终确定主题（精炼、定义及命名主题）。一旦确定了最终主题集，我们将其整合成一个与研究问题相一致的叙述（写作*up*).

因此，我们按照四个主题呈现结果：追踪跑步的动机、评估训练负荷、以及确定和改变训练负荷的来源，以回答第一个研究问题（跑者如何利用运动数据进行TLM？），以及对TLM中追踪器的信任，以回答第二个研究问题（他们如何看待和使用追踪器的TLM建议？）。

3.5 局限性

我们的访谈样本主要为男性和西方人，24名参与者中有15名男性。调查结果也显示出类似的性别分布（女性跑者N=85 名，男性跑者N=164 名）。

此外，虽然我们没有收集调查参与者的居住国信息，但由于招募主要集中于欧洲的一个本地马拉松赛事、本地跑步俱乐部以及作者的个人联系人，我们预计存在偏差。未来的研究可以探讨TLM实践在其他文化中的差异，以及性别分布更为均衡的样本。例如，

Niess等人 [66] 的一项研究比较了不同人口统计群体的健身追踪实践，表明阿拉伯用户更重视生理测量而非目标设定。这一偏好可能影响该群体对追踪器提供的指标和训练负荷管理建议的重视程度。

此外，我们的样本报告显示，其跑步经验的平均时长从6个月到50年不等。跑步者的经验水平可能会影响他们处理训练负荷管理和运动数据的方式。

文献指出，经验更丰富的跑者倾向于低估自身技能（而经验较少的跑者则相反：他们往往高估自身技能，参见[51, 52]）。然而在本文研究范围内，我们仅将此信息用于描述性分析，而非比较不同“自评跑步经验”的跑者如何管理训练负荷。

未来研究可以探讨新手和经验丰富的跑者是否以不同方式利用运动追踪器管理其训练负荷。

4 追踪器在训练负荷管理中的使用实践

本节将讨论我们的研究对跑者的训练负荷管理知识与实践、他们使用追踪器监测和管理训练负荷（研究问题1）以及他们对追踪器训练负荷管理相关建议的感知（研究问题2）所获得的洞察。总体而言，我们未发现访谈参与者与调查研究结果存在矛盾或分歧的案例。

但我们的访谈结果为追踪器如何融入跑者的训练负荷管理实践提供了更细致的视角。我们将按照表1所列问题的顺序，同时报告调查和访谈的发现。

4.1 跑步追踪动机

调查结果显示，跑步者热衷于“学习如何提升自我”（M=4.22，SD=0.81）。追踪跑步能让他们“在了解自我的过程中获得愉悦”（M=4.16，SD=0.85），并且是“提升表现的有效方式”（M=4.10，SD=0.86）。

他们“在追踪跑步时感觉更佳”（M=3.96，SD=0.93），并认为这是“实现自我发展”的良好途径（M=3.96，SD=0.96）。这些结果表明，我们的调查参与者具有追踪跑步的内在动机（所有调查项目详见表4）。

以“预防跑步相关伤害”为目的的跑步追踪极少成为主要关注点（M=2.32，SD=1.23）。

访谈结果支持了上述调查发现。绝大多数受访者（N=19）表示使用追踪器是为了观察备赛进展（如备战半程马拉松），并通过自我比较评估表现提升（例如对比赛前六个月与一个月的表现）。跑步追踪最显著的感知益处在于，各类跑步相关指标能让跑者评估自身表现（N=13）。例如P21这样描述：

> “我认为有一个概述是好的。在跑步中，它很快成为一种计划手段。如果你计划事情，你也想记录你所做的，看看你的实现是否与计划相同。回顾并观察模式非常有价值，无论它们是导致受伤还是你的表现有所进步。然后，你试图将你所做的与你是否进步或是否受伤联系起来。所以，我认为这些是最重要的原因。获得一块记录一切的手表是出于便利。我想在跑步过程中即时获取数据。手表是显而易见的入门方式。” *(P21,* 平均值*).*

追踪跑步的第二个主要动机是了解跑步行为（N=14）。一方面，跑步者对自己的表现指标以及技术能带来什么感到好奇（N=5）。另一方面，他们认为追踪器比他们的记忆更准确地记录跑步情况，从而支持更好的学习（N=11）。此外，根据我们的参与者，使用追踪器不仅基于指标评估表现，还关乎学习如何成为“更好的跑步者”。例如，近一半的参与者提到，追踪器提供的数据帮助他们更好地理解了

Table 4: Motivations for Running Tracking (*N*=249)*

	Motivations for Tracking	M	SD
IM	It is very interesting to learn how I can improve myself.	4.22	0.81
IM	Tracking gives me pleasure to learn more about myself.	4.16	0.85
IM	I find tracking is a good way to improve my performance.	4.10	0.86
IM	I feel better about myself when I track my runs.	3.96	0.93
IM	I have chosen to track my runs as a way to develop myself.	3.96	0.96
IM	Tracking my runs is an integral part of my life.	3.09	1.29
EM	I would feel bad about myself if I did not track my runs.	2.37	1.20
–	I track my runs to prevent running related injuries.	2.32	1.23
EM	Tracking my runs reflects the essence of who I am.	2.27	1.19
EM	Others would disapprove of me if I did not track my runs.	1.33	0.77
EM	The people I care about would be upset if I did not track my runs.	1.18	0.57

*IM refers to the items that measure intrinsic motivation, EM to extrinsic motivation. The item with – was not listed in the original scale.

rationale behind training suggestions given by their coaches or trackers (*N*=10).

Thirdly, runners would use their running data to compare it with their perceived running performance (*N*=13). Participants pointed out that the data's impact on motivation varies based on how well the data aligns with their perception of their running experience. Data occasionally leads to demotivation when there is a mismatch between tracked data and what the runner feels about their performance. Runners continue to track their runs despite this mismatch, as they rely more on their feelings than on data during data-feeling misalignments (see Section 4.4 for more details about this mismatch).

Another motivation for runners to track their runs is having a positive attitude, inherent affection for data and seeing running behaviours in numbers (*N*=9). In contrast with this affection, several participants noted that they typically do not look at their running data while running; nevertheless, they keep tracking their runs for future performance reflections (*N*=9). In simpler words, they are motivated to use trackers for "prospective reflections". Nonetheless, many runners track their runs for future reference. This practice resonates with documenting tracking, as outlined by [79], but differs from it: runners in our study do not only document their runs but also use them for future reflections, which can inform adjustments to their running behaviour. Especially for P20, tracking is to avoid missing values in their dataset: "*The problem is like Duolingo issue. . .* ***You do not want gaps in your data even if you do not use it****. That is, you know, data scientists' worst nightmare: the missing values. So,* ***to avoid those, I just use the watch all the time.***"

Other motivations for tracking runs include the sense of achievement and success runners feel after looking at their data, particularly when they see an improvement in their performance (*N*=7), adapting training load to prevent injuries (*N*=5) and recording running experience holistically by including factors beyond running metrics such as trail choices and favourite running spots (*N*=4). In sum, looking at the survey and the interview results together, it becomes apparent that runners have a desire to regulate their running behaviour to be better in what they do and utilise trackers to objectively capture running data that can be turned into actionable insights once it is combined with their experiences and feelings.

Table 5: The Perceived Importance of Metrics for Training Load Management

Metrics	M	SD
Average heart rate	3.90	1.07
Distance	3.83	0.95
Duration	3.76	1.05
Running Frequency	3.64	1.07
Instant pace	3.60	1.05
Average pace	3.60	1.05
Perceived intensity	3.55	1.07
Total weekly distance	3.52	1.06
Heart rate variability	3.36	1.19

4.2 Assessing Training Load with Tracker Metrics

In the survey, we asked participants about the importance of nine running-related metrics in assessing their training load. Among these metrics (Table 5), average heart rate was reported as the most important metric (*M*=3.90, *SD*=1.07), followed by distance (*M*=3.83, *SD*=0.95), and duration of runs (*M*=3.79, *SD*=1.05). HR variability was ranked as the least important metric for TLM, with a mean rating of 3.36 (*SD*= 1.19), yet above the middle score (i.e., 3.00) of the rating scale.

The interviews helped clarify why certain metrics were more prominent than others and provided a significant distinction between measured and derived metrics. When asked about the metrics checked before, during and after running, all participants reported checking at least one of the following: HR, distance, duration, and pace. In response to the same question, half of the participants mentioned looking at metrics such as VO_2Max (*N*=19) and power (*N*=10) data after running. Furthermore, we found that runners differentiate measured metrics, measured directly by the tracking device (e.g., HR), from derived metrics, which are calculated based on multiple measured metrics (e.g. recovery time). Interestingly, the number of participants who indicated a deliberate use of derived metrics when revising their training program (*N*=9) surpassed those who

表4: 跑步追踪动机 (N=249)*

	追踪动机	M	SD
IM	了解如何提升自我非常有趣。	4.22	0.81
IM	追踪让我愉悦地更了解自己。	4.16	0.85
IM	我发现追踪是提升我表现的好方法。	4.10	0.86
IM	当我追踪我的跑步时，我会对自己感觉更好。	3.96	0.93
IM	我选择追踪我的跑步作为自我发展的一种方式。	3.96	0.96
IM	追踪我的跑步是我生活中不可或缺的一部分。	3.09	1.29
EM	如果我不追踪我的跑步，我会对自己感到不满。	2.37	1.20
–	我追踪我的跑步是为了预防跑步相关伤害。	2.32	1.23
EM	追踪我的跑步反映了我本质的自我。	2.27	1.19
EM	如果我不追踪我的跑步，其他人会不赞同我。	1.33	0.77
EM	我在意的人会因我不追踪跑步而感到失望。	1.18	0.57

*IM指测量内在动机的项目，EM指外在动机。带–的项目未列入原量表。

教练或追踪器给出的训练建议背后的原理（N=10）。

第三，跑步者会利用他们的跑步数据进行对比
与其感知跑步表现(N=13)。参与者
指出数据对动机的影响因
数据与跑步者对其跑步体验的认知契合度而异。
当追踪数据与跑步者对其
表现的实际感受存在差异时，数据偶尔会导致动力丧失。
尽管如此，跑步者仍会继续追踪跑步数据，
因为他们更依赖自身感受而非数据。
在数据与感受不一致时（详见第4.4节获取更多细节
关于这种不匹配）。

跑步者追踪跑步行为的另一动机是持有积极态度、对数据的内在喜爱以及通过数字观察跑步行为（N=9）。与这种喜爱形成对比的是，部分参与者提到他们通常在跑步时不会查看跑步数据；尽管如此，他们仍持续追踪跑步行为以供未来表现反思（N=9）。简而言之，他们受"前瞻性反思"驱动而使用追踪器。然而，

许多跑步者为未来参考而追踪跑步行为。这一做法与[79]所述的记录追踪相呼应，但存在差异：我们研究中的跑步者不仅记录跑步行为，还将其用于未来反思，从而指导调整跑步行为。尤其对P20而言，追踪是为了避免数据集中出现缺失值："问题就像多邻国问题……即使不使用数据，你也不希望数据存在空白。

也就是说，你知道，数据科学家最害怕的就是缺失值。
所以为了避免这些，我就一直使用手表。"

追踪跑步的其他动机包括跑步者在查看数据后获得的成就感和成功感，尤其是当他们看到表现有所提升时（N=7）。

调整训练负荷以预防受伤（N=5），并通过纳入跑步指标之外的要素（如路线选择和最喜欢的跑步地点）来全面记录跑步经验（N=4）。综合调查和访谈结果可见，跑步者渴望规范自己的跑步行为以提升表现，并利用追踪器客观捕捉跑步数据，这些数据与他们的经验和感受结合后可转化为可操作的见解。

表5：训练指标的感知重要性
训练负荷管理

指标	M	SD
平均心率	3.90	1.07
距离	3.83	0.95
持续时间	3.76	1.05
跑步频率	3.64	1.07
即时配速	3.60	1.05
平均配速	3.60	1.05
感知强度	3.55	1.07
每周总距离	3.52	1.06
心率变异性	3.36	1.19

4.2 使用追踪器评估训练负荷指标

在调查中，我们询问了参与者九项跑步相关指标对评估训练负荷的重要性。这些指标中（表5），平均心率被报告为最重要的指标（M=3.90，SD=1.07），其次是距离（M=3.83，

标准差=0.95)，以及跑步时长（平均值=3.79，标准差=1.05）。心率变异性在训练负荷管理中被列为最不重要的指标，平均评分为3.36（标准差= 1.19），但仍高于评分量表的中间分数（即3.00）。

访谈帮助我们厘清了为何某些指标比其他指标更受关注，并清晰区分了测量指标与衍生指标。当被问及跑步前、中、后查看的指标时，所有参与者都表示至少会关注以下一项：心率、距离、持续时间和配速。针对同一问题，半数参与者提到跑步后会查看诸如最大摄氧量（N=19）和功率（N=10）数据等指标。此外，我们发现跑步者会区分由追踪设备直接测量的指标（例如，

心率），到衍生指标（这些指标基于多个测量指标计算得出，例如恢复时间）。有趣的是，在修订训练计划时有意使用衍生指标的参与者数量（N=9）超过了那些

used measured metrics ($N=4$). We discovered that this tendency is associated with runners' awareness of their performance and how training influences it. The following comment from P4 illustrates how a measured metric (e.g., pace) can become less important in time:

> *"When I started running,* ***I made all the usual mistakes that one can make, one of which is going too hard and too often****. So, the heart rate data was a bit high. At some point, I started to care about my heart rate. And I wanted to keep it below a certain number. That can be really frustrating...* ***But now I know what I can do, and on those days that I run without looking at the watch, I can predict within a few seconds what my actual pace is****. So, I do not really need to watch to know what pace I am running."* (P4, M).

With the advancement of technology, the derived metrics used in training load also become more important. For example, for P7, who was tracking his runs for four years, power data became more important than HR data about a year ago:

> *"Also, in the beginning, I used to check only my pace, for long runs and my heart rate for the interval training. And after, I believe, a year ago, I changed to another device and connected my Garmin watch to the Stryd foot pod. And Stryd foot pod calculates your power. I have to say I really love it.* ***I love it even more than my heart rate values****."* (P7, M).

Furthermore, we found that the runners' emotional and mental state during a specific workout (i.e., whether they are in the mood to run intensively) hold equal importance to both measured and derived metrics in assessing training load ($N=7$). For example, P2 explains how he prioritises bodily sensations over a derived metric:

> *"Because sometimes I run the day after training,* ***the watch still says "you need to recover"****. But my legs do not feel like they need recovery. Of course, after a very long distance (run), I give two days break, but I also know that some people run a marathon each day, but this is not for."* (P2, M).

Interestingly, a subset of runners incorporates biomechanical metrics into understanding the training load of their running workouts. These metrics encompass vertical ratio, which serves as an indicator of a runner's balance (e.g., P10); training stress score, which quantifies the stress imposed by each workout (e.g., P21); and training readiness, which signals a runner's physical preparedness to another running workout (e.g., P23). While these metrics do not serve as the primary sources for training load assessment for many runners, they provide additional TLM-related insights. For example, P10 emphasised the significance of the *average ground contact time balance*, portraying how the nuances of foot placement and road conditions impact her running balance. Her watch gives her feedback when there is too much imbalance, resulting in changing the side of the road she runs to address any imbalance issues. To sum up, these findings signal the intricate web of factors that runners consider when assessing training load, underlining the blend of objective data, subjective sensations, and evolving personal insights that shape their training journeys.

4.3 Sources for Determining Training Routines and Changes

Survey participants' responses regarding their training program preferences and sources (Table 6) show the highest mean value for the statement "*I schedule my own weekly training program myself*" ($M=3.43$, $SD=1.40$), suggesting a tendency for self-directed training planning. Conversely, the statement "*I follow a training program that my sports watch provides me*" ($M=1.46$, $SD=0.98$) and "*I follow a training program that a running app provides*" received the lowest mean score, indicating a reluctancy to adhere to training suggestions given by technology. The mean value for receiving "*training programs from a running coach*" ($M=2.41$, $SD=1.57$) was moderate (Table 6).

Survey results also showed that runners rely more on their intuition than the trackers suggest in changing their training plans (Table 7). They tend to "*listen to their body before going for a run*" ($M=3.76$, $SD=0.95$), "*decide the pace of their run based on how they feel during running*" ($M=3.72$, $SD=1.04$), "*trust their body signals while planning their running schedule*" ($M=3.68$, $SD=0.95$). Furthermore, runners are less inclined to "*decide the pace of their run based on the data the sports watch provides them during running*" ($M=2.86$, $SD=1.34$). Finally, they are less inclined to "*decide training schedule based on tracker's training suggestions*" ($M=1.84$, $SD=1.06$) and "*based on tracker's recovery hours suggestion*" ($M=1.84$, $SD=1.11$).

Through the interviews, we learned more about why runners tend to schedule their own training program and are not inclined to follow a training program provided by an app or a sports watch. We found that runners do not implement the training suggestions given by the tracker when (1) there is incompatibility between what the runner feels and what data tells; (2) they have a preference for feeling-driven training ($N=15$); (3) they do not want to feel an obligation towards complying with a "machine" (e.g., P5) ($N=4$); the watches or apps do not provide tailored training suggestions ($N=11$) nor realistic and believable predictions regarding performance and recovery time ($N=7$), and actionable training program suggestions ($N=3$). For example, P15 expresses her awareness of physical limits, especially when she feels pain in their knees. Then her judgment becomes "*just about the feeling and not about what I see in the app or something*".

Through the interviews, we discovered that determining and adapting a training program is a dynamic process for runners, which involves utilising different sources in different situations, feelings, data provided by trackers, coaches' suggestions, and normative training plans. We identified a tendency to prefer certain sources over others (e.g., relying more on one's feelings than tracker data when determining a training plan). The following sections present these sources from the most to the least preferred. However, this does mean that runners always stick with a single source when determining or adapting a training program. For instance, several participants mentioned that (e.g., P1, P5, P7). At the same time, they generally comply with training program suggestions made by their coaches. They also use their feelings to gauge the appropriateness of these suggestions.

使用测量指标的参与者（N=4）。我们发现这一倾向与跑者对其表现及训练如何影响表现的意识相关。以下来自P4的评论说明了测量指标（如配速）如何随时间变得不那么重要：

> "刚开始跑步时，我犯了所有初学者可能犯的错误，其中之一就是训练过度且过于频繁。因此，心率数据有些偏高。后来我开始关注自己的心率，并希望将其控制在某个数值以下。这确实令人沮丧...但现在我知道自己能做什么了，那些不戴手表跑步的日子里，我能在几秒内预测出实际配速。所以我不再需要依赖手表来了解自己的跑步配速。"（*P4*，平均值）

随着技术的发展，训练负荷中使用的衍生指标也变得更加重要。例如对于P7来说，

这位持续四年追踪跑步数据的跑者表示，约一年前功率数据已变得比心率数据更重要：

> "此外，刚开始时，我只查看长距离（跑步）的配速和间歇训练时的心率。大约一年前，我换了一台设备，将佳明手表与*Stryd*足部传感器连接。*Stryd*足部传感器会计算你的功率。我必须说我非常喜欢它，甚至比心率数值更让我喜爱。"（*P7*，平均值）。

此外，我们发现跑步者在特定锻炼期间的情绪和心理状态（即他们是否有心情进行高强度跑步）对于评估训练负荷的实测指标和衍生指标具有同等重要性（N=7）。例如，P2解释了他如何优先考虑身体感觉而非衍生指标：

> "因为有时我在训练后的第二天跑步，手表仍显示'你需要恢复'。但我的双腿并不觉得需要恢复。当然，在完成一次非常长距离（跑步）后，我会休息两天，但我也知道有些人每天跑马拉松，但这并不适合我。"（*P2*，平均值）。

有趣的是，一部分跑步者会结合生物力学指标来理解他们跑步锻炼的训练负荷。这些指标包括作为跑者平衡指标的垂直比例（例如P10）、量化每次锻炼所施加压力的训练压力分数，

以及反映跑者对下一次跑步锻炼身体准备状态的训练准备度（例如P23）。虽然这些指标并非多数跑步者评估训练负荷的主要依据，但它们提供了额外的与训练负荷管理相关的见解。

例如，P10强调了平均触地时间平衡的重要性，描述了足部放置的细微差别和路况如何影响她的跑步平衡。当出现过度不平衡时，她的手表会提供反馈，促使她改变跑步的马路侧边以解决任何不平衡问题。总之，这些发现表明了跑步者在评估训练负荷时所考虑的复杂因素网络，凸显了

客观数据、主观感受与动态变化的融合
塑造其训练历程的个人见解。

4.3 确定训练计划的来源 及调整依据

调查参与者关于其训练计划偏好及来源的回复（表6）显示，"我自行安排每周训练计划"这一陈述的平均值最高。

(平均值=3.43, 标准差=1.40)，表明存在自主训练规划的倾向。相反，"我遵循运动手表提供的训练计划"(平均值=1.46, 标准差=0.98)和"我遵循跑步应用提供的训练计划"这两项陈述获得了最低平均分数，显示出对技术提供的训练建议存在抵触。而"接受跑步教练提供的训练计划"的平均值(平均值=2.41, 标准差=1.57)处于中等水平(表6)。

调查结果还显示，跑步者在更改训练计划时更依赖自身直觉而非追踪器建议(表7)。他们倾向于"在跑步前倾听身体感受"

*(*平均值=3*.76,* 标准差=0*.95)*、"根据跑步时的身体感觉决定配速*"(*平均值=3*.72,* 标准差=1*.04)*、"在规划跑步日程时信任身体信号*"(*平均值=3*.68,* 标准差=0*.95)*。此外，跑步者较少倾向于"根据运动手表在跑步过程中提供的数据决定配速*"(*平均值=2*.86,*

标准差=1*.34*）。最后，他们不太倾向于"根据追踪器的训练建议决定训练计划"（平均值=1*.84*，标准差=1*.06*）以及"基于追踪器的恢复时间建议"（平均值=1*.84*，标准差=1*.11*）。

通过访谈，我们进一步了解到为何跑步者倾向于自行安排训练计划，而不愿遵循应用程序或运动手表提供的训练计划。

我们发现，跑步者在以下情况下不会执行追踪器提供的训练建议：（1）跑步者的感觉与数据所示存在不兼容；（2）他们偏好感觉驱动的训练（否=15）；（3）他们不愿感到必须服从"机器"（例如，P5）（否=4）；（4）手表或应用程序未提供定制训练建议（否=11），也未给出关于表现和恢复时间的现实且可信的预测（否=7），以及可操作的训练计划建议（否=3）。例如，P15表达了她对身体极限的认知，

尤其是当她感到膝盖疼痛时。此时她的判断就变成了"几乎全凭感觉，而不是我在应用程序或其他地方看到的数据"。

通过访谈，我们发现制定和
调整训练计划对跑步者而言是一个动态过程，
涉及在不同情境下运用多种来源：个人感受、
追踪器提供的数据、教练建议以及规范
训练计划。我们注意到跑步者更倾向于优先采用某些特定来源。
优于其他（例如，更多地依赖个人感受而非追踪器数据
来制定训练计划）。以下部分按从最偏好到最不偏好的顺序
呈现这些来源。但这并不意味着跑步者在确定或调整
训练计划时总是坚持单一来源。例如，几位
参与者提到（如P1、P5、P7）。与此同时，他们
参与者提到（例如，P1、P5、P7）。与此同时，他们
通常遵循教练制定的训练计划建议。
他们也会利用自身感受来评估适当性。
这些建议中的。

Table 6: Source Use for Planning Running Workouts

Question	M	SD
I schedule my own weekly training program myself.	3.43	1.40
I receive a training program from a running coach.	2.41	1.57
I do not follow a structured training program.	2.30	1.51
I follow the training suggestions a runner friend provides me.	1.78	1.19
I follow a training program that a running app provides.	1.75	1.28
I follow a training program that my sports watch provides me.	1.46	0.98

Table 7: Sources for Change in Running Training

Question	M	SD
I listen to my body before going for a run.	3.76	0.95
I decide the pace of my run based on how I feel during running.	3.72	1.04
I trust my body's signals while planning my running schedule.	3.68	0.95
I decide the pace of my run based on the data my sports watch provides me during running.	2.86	1.34
I decide my training schedule based on my tracker's training suggestions.	1.84	1.06
I decide my training schedule based on my tracker's recovery hours suggestions.	1.84	1.11

4.3.1 Learning with Data, Knowing by Feel. We found that the most prevalent approach for runners in determining or adapting their training program was relying on their bodily sensations at a given time, such as being tired, fatigued or stimulated (*N*=17). Interviews demonstrated that most runners have a profound understanding of how their body responds to a running workout and that such self-awareness makes them confident in determining or adapting their training program themselves. The comment below showcases the shared understanding among runners that their body signals are more reliable indicators than what a tracker tells.

> *"I just know what the response is from my body if I run too fast. I listen to my body, and I think I understand my body's reactions quite well now. So, if I feel I am getting tired, I slow down a little bit. I do a little more if I have some headroom and can do a little more.* ***My body tells me much better, in my opinion, than the watch****."* (P12, M).

Runners also acknowledge that their perceived competence in determining training load by feel accumulates in time with the help of trackers. In his later comments, P12 pointed out that "*the technology can help get a relation between* ***how it actually goes and how you feel***", and that the tracker assists him in learning to listen to his body and react to it. In a way, the trackers' primary function becomes providing a ground truth to runners, helping them see their performance more objectively. For example, P17 stated the following:

> *"I did not use a training plan supported by the watch. But* ***I learned to read the information*** *the watch provides about heart rate, distance, speed, and cadence, and I translated them into my (marathon) training plan. So, after the marathon,* ***I look back on the information the watch provides and my feel and (reflect on) what is good and what went well****. Um, do I need to try more? Do I need to train less? Do I need to train in different sessions?"* (P17, M).

This approach of learning through data proved to be instrumental for injury prevention, as described by P21:

> *"When I see (injury is) in onset, I try to be very proactive there. I think I got better and not getting that (injury) at all, and I think the Training Peaks and* ***all the metrics helped a lot in that****. And every once in a while, you feel the niggle, something starts showing up, and if that's something that led to an injury earlier, you know what it is."* (P21, M).

Yet, as P13 highlighted, suggestions provided by trackers might contradict their perceived efforts when a tracker indicates an "acceptable level of training load", but the runner feels that the workout was too difficult to be at an acceptable level. In such situations, runners often prioritise suggestions leaning towards recovery. Such judgements lead to adopting the mantra "*no training is also training*" (P13), recognising the value of recovery in injury prevention.

4.3.2 Incorporating Trackers' Suggestions in TLM Decision-Making. The preference for feeling-driven training does not mean that runners completely ignore their trackers when determining or adapting their training program. For instance, some runners mentioned that they regard tracker suggestions as advice, meaning they incorporate them into their training plans while ultimately relying on their feelings (*N*=14). Furthermore, some tend to follow the tracker recommendations during their initial tracking phases and, in time, become more knowledgeable about the training load and their own bodies. During this process, they consider these suggestions mere advice rather than strict mandates. The comment of P7 encapsulates this transition:

> *"I followed my weight and my morning heart rate just to see if I was overtraining; you might lose weight, and your heart rate in the morning might be too low or too*

表6：跑步训练计划来源使用情况

问题	M	SD
我自己安排每周的训练计划。	3.43	1.40
我从跑步教练那里获得训练计划。	2.41	1.57
我不遵循结构化的训练计划。	2.30	1.51
我遵循跑友提供的训练建议。	1.78	1.19
我遵循跑步应用提供的训练计划。	1.75	1.28
我遵循运动手表提供的训练计划。	1.46	0.98

表7：跑步训练变化的来源

问题	M	SD
跑步前我会倾听身体的信号。	3.76	0.95
我会根据跑步时的感觉决定跑步速度。	3.72	1.04
制定跑步计划时我相信身体的信号。	3.68	0.95
我会根据运动手表提供的实时数据决定跑步速度。	2.86	1.34
我会根据追踪器的训练建议制定训练计划。	1.84	1.06
我会根据追踪器的恢复时间建议制定训练计划。	1.84	1.11

4.3.1 数据学习，感知认知。我们发现最跑步者在决定或调整其训练计划时普遍采用的方法是依赖特定时间下的身体感觉，例如感到疲倦、疲劳或兴奋（N=17）。访谈表明大多数跑步者对自身如何响应跑步锻炼有深刻理解，且这种自我意识使他们有信心决定或调整他们自己制定训练计划。下面的评论展示了跑步者之间达成的共识，即他们的身体信号比追踪器提供的数据更能可靠地反映实际情况。

> "我只是知道如果我跑得太快，我的身体会有什么反应。我倾听身体的声音，并且我认为我现在相当了解身体的反应。所以，如果我感到疲倦，就会稍微放慢速度。如果还有余力，我会多做一点。在我看来，我的身体比手表更能准确地告诉我这些。"（*P12*，平均值）。

跑步者也承认，他们通过感觉来确定训练负荷的感知能力会随着时间积累。追踪器的帮助下。P12在后续评论中指出，"该技术能帮助建立实际状况与主观感受之间的关联，追踪器协助他学习倾听身体信号并作出反应。某种程度上，追踪器的主要功能转变为向跑步者提供基本事实，帮助他们更客观地看待自身表现。例如，P17表示他们的表现可以更客观地评估。例如，P17指出，如下：

> "我没有使用手表支持的训练计划。但我学会了读取手表提供的心率、距离、速度和步频信息，并将它们转化为我的（马拉松）训练计划。
>
> 因此，在马拉松比赛后，我回顾手表提供的信息以及我的感受，并（反思）哪些方面做得好、哪些进展顺利。嗯，我是否需要尝试更多？是否需要减少训练量？是否需要以不同的训练单元进行？"（*P17*，平均值）。

这种通过数据学习的方法被证明非常有效，正如P21所描述的伤害预防方面：

> "当我发现（受伤）即将发生时，我会非常积极地应对。我认为我在这方面做得更好，甚至完全避免了受伤，我觉得*Training Peaks*和所有指标在这方面帮助很大。偶尔你会感觉到一些小问题开始显现，如果这是之前导致受伤的原因，你就知道它是什么。"（*P21*，*M*）。

然而，正如P13所强调的，当追踪器显示"训练负荷处于可接受水平"而跑步者感觉锻炼过于困难、难以达到可接受水平时，追踪器提供的建议可能与他们的感知努力相矛盾。在这种情况下，

跑步者通常会优先考虑倾向于恢复的建议。这种判断导致他们采纳"不训练也是一种训练"的信条

（P13），认识到恢复在伤害预防中的价值。

4.3.2 将追踪器建议纳入*TLM*决策制定

对感觉驱动训练的偏好并不意味着跑步者在确定或调整训练计划时完全忽视追踪器。例如，一些跑步者提到他们将追踪器建议视为建议，意味着他们会将这些建议纳入训练计划，但最终仍依赖自己的感受（N=14）。此外，一些人在初始追踪阶段倾向于遵循追踪器推荐，随着时间的推移，

他们对训练负荷和自己的身体有了更多了解。在这个过程中，他们认为这些建议仅仅是建议，而非严格的指令。P7的评论概括了这一转变：

> "我跟踪我的体重和晨间心率，只是为了看看我是否在过度训练；你可能会体重下降，而且你的晨间心率可能过低或过高，与平均值相比。

> *high compared to the average. That happened a couple of years ago when I was training for my first marathon. Still, I am continuously monitoring my weight and morning heart rate, but* ***even if I see some stability in data, my decision is more based on my feel than my watch****."* (P7, M).

Runners' compliance with the tracker's training load suggestions is related to the perceived usefulness of these suggestions, which is increased when they are presented in a comprehensible manner (*N*=9), tailored to runners' experience and knowledge in training load (*N*=6), and represent different time intervals (*N*=2). Such tailored tracker suggestions, however, cannot reflect outside factors that affect the quality of a running workout. Therefore, runners' decisions during and within the activity are sometimes less dependent on their in-act data. P14 exemplifies how weather conditions can affect the effort they put into a workout:

> *"(My decision to change the workout) mostly depends on the weather. When you go to the beach, it is often very windy, and your speed depends on the wind direction. I start with running in my face and end with the wind in my back. Because you have to run back, and if you are tired and still have the wind in your face, (running) turns very hard sometimes."* (P14, M).

4.3.3 Customising Normative Training Plans. We found that some runners (*N*=10) would customise training plans received from apps, online resources, and athletic clubs. This way of customising normative training plans allows them to change the workout days or the intensities based on their daily routines. Trackers play a role in this adoption when runners use the "recommended workout" function of the trackers. Such functions enable planning their own interval training workout. Some runners perceive these functions as "handy", while others might consider that their trackers do not support customisation that well. Some runners also register for a target race (e.g., a road half marathon or a hilly trail race) (*N*=10) and use this target race as the end of their training planning and adjustments. In making these adjustments, the data can play a role in making the training program better, as described by P23, whose aim was to be in the top 10 of a very competitive race:

> *"I mostly make training programmes for a target race. First, I define a target. Then I make the programme mostly for a year or a season. That programme is only the base. Each month and each week, I look into my data and adjust the weekly training plan. After all,* ***I make the base programme for each target race much better while training.****"* (P23, M).

The interviews revealed that runners considered various factors when customising their training plans, which include the runner's preferred style of training (e.g., how much they want to push themselves) (*N*=4) and the level of exertion needed (e.g., being in an aerobic and anaerobic zone) (*N*=4). For example, P13, who was very much into running long-distance races, stated that after several years of working with a coach, she concluded that slow runs were unsuitable. Therefore, she replaced workouts involving intervals, longer runs with speed variations, or changes in pace because she believed these methods led to better results in her running.

4.3.4 Planning Training Load with a Coach. Sometimes, runners work with a human coach who determines their training program and adjusts the planning together with the runner (*N*=10). In such cases, the tracker data becomes a communication medium between the coaches and the runners. The runners are engaged in discussions with the coach and negotiate with them to decide what is best for their health and goals. In most cases, they use a combination of tracker and input from the coach to determine the right training. The comment from P1 illustrates this:

> *"Well, I do have a running coach. That helps me plan my running. But then again, that's the planning, and I always try, and say: Okay, does this planning feel right?* ***Does it feel right based on how I feel, but also does it feel right based on the metrics that I see on my watch, on my Strava, on Training Peaks****?"* (P1, M).

Even though the survey results and interviews highlighted that runners are reluctant to follow a training plan from a virtual coach in managing their training load, the openness to such kinds of sources for TLM might depend on the runners' preferences. For example, P16, working with a human coach at the time of the interviews, indicated that she completed a training program provided by Garmin AI coach twice. However, her reason for transitioning from AI coach to human coach was to improve her performance with someone who knew better than her. In her own words, working with a human coach was "*accepting the convenience of having someone who could know better*", implying that a virtual coach cannot know better than a human coach.

4.4 Trust in Trackers in Training Load Management

In the survey, we inquired into participants' trust in the data and suggestions displayed by trackers. We found that runners mostly trust technology in accurately measuring their training metrics (*M*=3.92, *SD*=0.95), with their trust level decreasing in training load (*M*=3.01, *SD*=1.13) and recovery time calculations (*M*=2.51, *SD*=1.19). This finding was also supported by the interview results, which indicated that whether a metric is measured directly by the tracker (HR) or derived from multiple metrics (e.g., energy level) influences runners' trust in this data. Accordingly, rather than its precision, runners like P11 trust "the trend" in the derived metric (e.g., VO_2Max). The main reasons for less trust in such derived metrics are, on the one hand, the lack of transparency on how a derived metric is calculated (*N*=8) and whether this calculation is based on a rigorous method (*N*=9), and on the other hand, the belief that inaccuracy of a measured metric will be multiplied when it is used to calculate a derived metric (*N*=5). P10 illustrates this situation with the following comment:

> *"When Garmin became more capable of measuring and* ***showing performance metrics****, I also became interested in them. I am still a fan of them, but my* ***heart rate data is not always accurate*** *because it is irregular, even during rest. Yet Garmin says (after running), "You ran too hard or too far, too fast". And "take two or three days of rest". I cannot use this suggestion (recovery time) because they look at my heart rate data, which is inaccurate."* (P10, F).

> 这种情况几年前在我为第一次马拉松训练时发生过。尽管如此，我仍在持续监测我的体重和晨间心率，但即使我在数据中看到一些稳定性，我的决定更多是基于我的感觉而非手表。”（*P7*，平均值）。

跑步者对追踪器训练负荷建议的依从性，与这些建议的感知有用性相关，

当建议以易于理解的方式呈现（N=9）、根据跑步者在训练负荷方面的经验和知识量身定制（N=6），并代表不同的时间间隔（N=2）时，这种感知有用性会增强。

然而，此类量身定制的追踪器建议无法反映影响跑步锻炼质量的外部因素。因此，

跑步者在活动期间和活动中的决策有时较少依赖于他们的实时数据。P14举例说明了天气条件如何影响他们在锻炼中投入的努力：

> “（我改变锻炼的决定）主要取决于天气。当你去海滩时，通常风很大，而你的速度取决于风向。我一开始是逆风跑，最后顺风跑。因为你必须跑回来，如果你已经累了却还逆风，（跑步）有时会变得非常艰难。”（*P14*，平均值）。

4.3.3 定制规范性训练计划。我们发现一些跑步者（N=10）会定制从应用程序、

在线资源和运动俱乐部收到的训练计划。这种定制规范训练计划的方式允许他们根据日常作息调整锻炼天数或强度。当跑步者使用追踪器的“推荐训练”

功能时，追踪器在此过程中发挥作用。此类功能使他们能够规划自己的间歇训练。一些跑步者认为这些功能“方便”，而其他人可能认为他们的追踪器对定制的支持不够好。一些跑步者还会报名参加目标赛事（如公路半程马拉松或山地越野赛）（N=10），并将此目标赛事作为训练规划和调整的终点。在做出这些调整时，数据可以帮助优化训练计划，正如P23所述，其目标是在竞争激烈的赛事中进入前十名：

> “我主要为目标赛事制定训练计划。首先，我会设定一个目标。然后，我通常会制定为期一年或一个赛季的计划。该计划仅是基础框架。每月和每周，我都会分析数据并调整周训练计划。最终，在训练过程中，我会针对每个目标赛事不断完善基础计划。”（*P23*，平均值）。

访谈显示，跑步者在定制训练计划时会综合考虑多种因素，包括跑步者偏好的训练风格（例如他们想要突破自我的程度）（N=4）以及所需的exertion水平（例如处于有氧和无氧区域）（N=4）。例如，热衷长跑比赛的P13表示，在与教练合作数年后，她认为慢跑并不适合自己，因此用间歇训练替代了相关锻炼。

她认为长跑结合速度变化或配速调整能带来更好的跑步效果，因此采用了这些训练方法。

4.3.4 与教练共同规划训练负荷。跑步者有时会与人类教练合作，由教练制定训练计划并与跑步者共同调整规划（N=10）。在此类情况下，追踪器数据成为教练与跑步者之间的沟通媒介。跑步者会与教练展开讨论并协商，共同决定最有利于其健康和目标的方案。多数情况下，他们会综合运用追踪器数据和教练建议来确定最佳训练方案。

P1的评论印证了这一点：

> “我确实有一位跑步教练，这帮助我规划跑步训练。但话说回来，那只是计划，我总是会尝试并自问：这个计划感觉对吗？不仅基于我的主观感受，还要结合手表、*Strava*和*Training Peaks*上的指标数据来判断？”（*P1*，平均值）。

尽管调查结果和访谈都强调跑步者不愿遵循虚拟教练提供的训练计划来管理他们的训练负荷，但对这类训练负荷管理来源的接受度可能取决于跑步者的个人偏好。例如，P16在访谈时正与一名人类教练合作，她表示自己曾两次完成由Garmin AI教练提供的训练计划。然而，她从AI教练转向人类教练的原因是为了在更懂行的人的指导下提升表现。用她自己的话说，与人类教练合作是“接受有人能更懂行的便利”，暗示虚拟教练无法比人类教练更懂行。

4.4 对追踪器在训练负荷管理中的信任

在调查中，我们询问了参与者对追踪器所显示数据和建议的信任程度。我们发现跑步者大多信任技术能准确测量他们的训练指标（M=3.92，标准差=0.95），但他们对训练负载（平均值=3.01，标准差=1.13）和恢复时间计算（平均值=2.51，标准差=1.19）。这一发现也得到了访谈结果的支持，这表明一个指标是否被直接测量追踪器（心率）或源自多项指标（如能量水平）影响跑步者对这些数据的信任。因此，与其精确度，像P11这样的跑步者信任衍生指标中的“趋势”。（例如最大摄氧量）。对此类衍生指标信任度较低的主要原因，一方面在于缺乏关于衍生指标如何计算的透明度（N{v1}），以及该计算是否基于严格方法（N=8）；另一方面则源于一种认知：测量指标的不准确性会在其用于计算衍生指标时被放大（N{v1}）。P10展示了这一现象（N=5）。情况附有以下评论：

> “当佳明设备能够更全面地测量和展示表现指标时，我也开始对这些指标产生了兴趣。我至今仍是它们的拥趸，但我的心率数据并不总是准确，因为它即使在休息时也波动不定。然而佳明却会在跑步后提示‘您跑得太拼或太远、太快’，并建议‘休息两三天’。我无法采纳这个恢复时间的建议，因为它是基于我不可靠的心率数据得出的结论。”（*P10*，*F*）。

The most prominent factor influencing trust in data is the accuracy in measuring a metric (*N*=20), along with the alignment between multiple measures of the same metric across time (*N*=6) and alignment between metrics measured by different devices (e.g., measuring one's heart rate through a chest sensor and smartwatch sensor) (*N*=4). The interview results indicate that accuracy is not only about measuring the metrics. Some participants mentioned that the validity of tracker predictions (e.g., race predictions) and suggestions (e.g., recovery time) increases their trust in these devices (*N*=15). There were also some instances where runners lost confidence in the accuracy of the trackers. The comment of P16 illustrates this:

> *"In some watches, there's a lot of GPS jumping. For instance,* ***it might show that I ran a kilometre in 2 minutes****. When I see this happening in 2-3 workouts in a row,* ***I lose confidence in the watch's accuracy*** *after a while."* (P16, F).

We also found that many runners use additional sensors to manage their training load precisely. For example, five runners explicitly indicated using a heart rate chest band to measure their training HR accurately. Still, others consider a few beats per minute imprecision in their HR data as not vital, as was stated by P14 that "5% more accuracy" is not very important.

The second most prominent factor influencing trust was the compatibility between what the runner feels and what the data tells. Compatibility then depends on the runner's agreement level with the data (*N*=15), as also elaborated on previously. We discovered that runners tend to compare the tracker data with their in-act experiences (e.g., comparing pace data provided by the tracker with perceived pace). They build trust in time if the gap between what is measured and felt is small (*N*=2). Furthermore, we found that runners do not merely subordinate themselves to the objective data that trackers provide them; instead, they consider the effort they put into diverse running workouts (i.e., easy, long or interval training). They attend to the post-workout somatic signals their body gives them. At times, they leverage the measured (e.g., heart rate) or derived (e.g., recovery time) metrics as informative cues in tailoring and fine-tuning their next workout. In other words, regarding trust in data, they try to see the bigger picture by comparing metrics and data sources. The case of P21 illustrates this nicely:

> *"Let's put it like this:* ***It is never just data I look at.*** *It is always a* ***combination of several metrics and my feelings****. If one is off, I look at the other ones,* ***and there's always a total picture****. And if something is not good during training, it is not just the watch telling me; I will also feel it. And that's fine because it happens every once in a while. If it happens a few trainings in a row, then something's wrong, and you should do something about it. But* ***it's not the watch that throws me out of balance****."* (P21, M).

Finally, survey results show that runners' trust in the accuracy of their data is essential for better TLM. We did a correlation analysis to understand how runners change their running routines based on training load-related suggestions from trackers. The results showed that runners' overall trust in trackers positively affects how they use them in planning and making decisions on their tracking. They tend to follow trackers' recovery time suggestions when they trust in trackers to accurately calculate their training load ($r(249)$=0.34 p<0.05, two-tailed) and recovery time ($r(249)$=0.49, p<0.05, two-tailed). Correlation analysis also showed that runners who trust their trackers to calculate their training load correctly are more likely to follow suggestions their tracker provides ($r(249)$= 0.23, p<0.05, two-tailed).

5 DISCUSSION

Through the deployment of a survey and interviews, we aimed to understand runners' use of sports trackers in their TLM practices. Overall, we discovered that these practices are dynamic, representing diverse relations between runners and their trackers in managing training load. During initial experiences in running, runners rely more on trackers and use them to gain insights into their performance. In time, they become more attuned to the signals of their body and learn, partially through the data, to better interpret these signals. Thus, their reliance on trackers reduces, and they start compensating for potential data flaws and inaccuracies in the data with their bodily sensations. Furthermore, our research, especially in the case of TLM, has revealed that runners engage in two types of TLM: Guided and Self-Directed TLM, differing in terms of the purpose of sports tracker use, sources for determining and adapting training routines and the role of technology in TLM.

In **Guided TLM** (Table 8), a runner aims to develop competency in TLM by learning from various sources. These include (1) running related data provided by trackers in the form of measured metrics (i.e., metrics based on the measurement of a single metric such as HR) and derived metrics (i.e., metrics calculated based on multiple measured metrics., such as VO_2Max); (2) body signals such as feeling exhausted; (3) training-related suggestions of virtual or human coaches, and (4) TLM-related normative information found in online sources or apps. In this type of TLM, runners elaborate on their running performance by comparing their somatic signals with running related data, which in turn helps them understand what these metrics mean for their performance. In some cases, this process of learning about the self is supported by a human or virtual coach, who makes training suggestions based on runners' performance measures, subjective experiences (e.g., perceived effort and fatigue) and training preferences. Thus, in Guided TLM, sports trackers work as data provider or workout advisor.

In **Self-directed TLM**, runners aim to decide the best training plan for them and be autonomous in TLM. In this type of TLM, they rely on their bodily signals to determine or adapt their training plans. In a way, data becomes less critical for TLM as the runner transitions from Guided-TLM to Self-directed TLM. Technology's role as the data provider remains, but runners start to perceive the role of technology more like a supporter, which confirms their decisions and bodily signals rather than an advisor suggesting t what to do.

In their research, Rapp and Tirabeni [72] identified a trend among amateur athletes towards self-coaching. Our findings extend these insights, showing that amateur runners also work with trainers [72, 73]. While there are parallels between our results and the prior work, notable differences emerge in data interpretation, sensory experiences, and coaching methodologies. We propose that TLM

影响对数据信任的最主要因素是测量指标时的准确性（N=20），以及同一指标随时间推移多次测量间的一致性（N=6），还有不同设备所测指标间的一致性（例如，

通过胸部传感器和智能手表传感器测量心率）（N=4）。访谈结果表明，准确性不仅关乎指标测量。部分参与者提到，追踪器预测（如比赛预测）和建议（如恢复时间）的有效性会增强他们对这些设备的信任（N=15）。但也存在跑步者对追踪器准确性失去信心的情况。P16的评论说明了这一点：

> "有些手表会出现严重的*GPS*漂移。比如，它可能显示我*2*分钟跑完一公里。当我连续*2-3*次锻炼都看到这种情况时，久而久之就会对手表的准确性失去信心。"（*P16，F*）

我们还发现许多跑步者使用额外传感器来精确管理训练负荷。例如，五位跑步者明确表示使用心率胸带准确测量训练心率。但也有人认为心率数据每分钟几拍的误差并不重要，正如P14所说'5%的更高准确性'并不非常关键。

影响信任的第二大因素是
跑步者自身感受与数据反馈之间的兼容性。
这种兼容性取决于跑步者对数据的一致程度
(N=15)，如前所述。我们发现
跑步者倾向于将追踪器数据与实际体验
进行对比（例如，将追踪器提供的配速数据与
感知配速）。如果测量数据与感受之间的差距较小（N{v1}），它们会随时间建立信任。此外，我们发现

跑步者并非仅仅屈从于追踪器提供的客观数据；相反，他们会考量自己在多样化
跑步训练（如轻松、长距离或间歇训练）中所投入的努力。
他们关注锻炼后身体发出的躯体信号，
转化为多样化的跑步训练（即轻松、长距离或间歇训练）。
他们关注身体在锻炼后发出的躯体信号。
他们。有时，他们会利用测量到的（例如心率）或
衍生的（例如恢复时间）指标作为信息线索，来定制
并微调下一次锻炼。换句话说，关于对数据的信任，
他们试图通过比较指标和数据源来了解整体情况。
P21的案例很好地说明了这一点：

> "这么说吧：我从来不会只看单一数据。这总是多个指标与我的感受共同作用的结果。若某一项异常，我会查看其他指标，总能获得整体认知。当训练中出现问题时，不仅是手表在提醒我，我自己也能感觉到。这很正常，因为偶尔发生无妨。但如果连续几次训练都如此，那就说明有问题需要调整。不过，让我失衡的从来不是手表本身。"（*P21*，平均值）。

最后，调查结果表明，跑步者对其数据准确性的信任对于更好的训练负荷管理至关重要。我们进行了相关性分析，以了解跑步者如何根据追踪器提供的与训练负荷相关的建议改变他们的跑步习惯。结果显示，跑步者对追踪器的整体信任度正向影响他们在规划和决策中使用追踪器的方式。他们倾向于在信任追踪器准确计算其训练负荷（r(249)=0.34 p<0.05，双尾）和恢复时间（r(249)=0.49，p<0.05，双尾）时，遵循追踪器的恢复时间建议。相关性分析还显示，那些信任追踪器能正确计算其训练负荷的跑步者更有可能遵循追踪器提供的建议（r(249)= 0.23，

p<0.05，双尾检验）。

5 讨论

通过开展调查和访谈，我们试图理解跑步者在训练负荷管理实践中对运动追踪器的使用情况。

总体而言，我们发现这些实践具有动态性，体现了跑步者与追踪器在管理训练负荷时形成的多元关系。在跑步初期，跑步者更依赖追踪器，并借此获取关于自身表现的洞察。随着时间推移，他们逐渐更敏锐地感知身体信号，并部分通过数据学会更好地解读这些信号。因此，他们对追踪器的依赖减少，并开始用身体感觉来弥补数据可能存在的缺陷与不准确性。此外，我们的研究还发现，

特别是在训练负荷管理（TLM）方面，研究发现跑步者采用两种类型的TLM：指导式和自主训练负荷管理。这两种方式在运动追踪器的使用目的、确定和调整训练计划的来源以及技术在训练负荷管理中的作用方面存在差异。

在指导式训练负荷管理（表8）中，跑者的目标是培养能力。
在训练负荷管理中，通过从多种来源学习。这些包括（1）由追踪器以测量形式提供的跑步相关数据。

指标（即基于单一指标测量的指标
例如心率（HR）和衍生指标（即基于计算得出的指标）
多项测量指标（如最大摄氧量）；(2) 身体信号，例如
如感到疲惫；(3) 虚拟或
人类教练提供的训练相关建议，以及(4) 从在线来源或应用程序中获取的训练负荷管理规范性信息。
在此类训练负荷管理中，跑步者通过将躯体信号
与跑步相关数据进行比较，从而详细分析他们的跑步表现，
这有助于他们理解这些指标对其表现的意义。在某些情况下，
这些指标对他们表现的意义。在某些情况下，
这一关于自我认知的学习过程由人类或
虚拟教练支持，后者根据跑步者的
表现测量、主观体验（如感知努力
与疲劳）及训练偏好提出训练建议。因此，在指导式训练负荷管理中，运动
追踪器充当数据提供者或锻炼顾问的角色。

在自主训练负荷管理中，跑步者旨在自行决定最佳训练
为他们制定计划并在训练负荷管理中保持自主性。在这种类型的训练负荷管理中，他们
依靠身体信号来决定或调整他们的训练
计划。某种程度上，随着跑步者从引导式TLM转向自主训练负荷管理，数据对训练负荷管理的重要性降低。技术作为
数据提供者的角色依然存在，但跑步者开始将
技术的作用更多地视为支持者，这确认了他们的
技术的作用更像是一个支持者，这证实了他们的
决策和身体信号而非顾问建议
该做什么。

Rapp和Tirabeni [72] 在其研究中发现业余运动员
倾向于自我指导的趋势。我们的发现延伸了这些
洞察，表明业余跑步者也会与教练合作
[72, 73]。尽管我们的结果与先前研究存在相似之处
工作方面，数据解读与感官体验上出现了显著差异
经验与指导方法。我们提出TLM

Table 8: Runners' TLM practices and technology's role in these practices

	Type of TLM	
	Guided TLM	Self-directed TLM
Purpose for sports informatics use:	Building competence in TLM Learning from various sources	Being autonomous in TLM
Sources for determining and adapting training routines:	Running related data Somatic signals Coaches Normative training plans	Somatic signals
The role of technology in TLM:	Data provider Advisor	Data provider Supporter

should be viewed as a dynamic, evolving process and found that runners develop their TLM competencies over time, gradually becoming more autonomous. This progression is not strictly tied to runners' status as amateur or elite athletes; instead, it hinges on effectively utilising data. This involves ongoing reflection on personal experiences to enhance TLM proficiency. Hence, our findings indicate that self-coaching, or as we term it, "self-directed TLM", is not exclusively the domain of either amateur or elite athletes. Instead, it emerges as a function of growing competence in TLM. This competence is cultivated over time through continuous interaction with personal data, requiring individuals to interpret it in the context of their physical sensations.

Our work also revealed friction between runners' knowledge about training load, their trust in their trackers' and their compliance with trackers' TLM recommendations (i.e., the importance given to data for managing training load or runners' tendency to lose trust in data when their experience is not aligned with it, as discussed in Section 4.4). Furthermore, although current sports trackers provide essential TLM-related data, runners do not always rely on those (e.g., the case of feeling-driven training, as discussed in Section 4.3.1). Considering these findings, we see several challenges and opportunities for SportsHCI research in improving sports tracking in TLM practices. We discuss these by referring to the relationship between performance metrics and subjective experiences, training load beyond performance data, and runners' trust in trackers in managing their training. Finally, we discuss the potential benefits of an ongoing dialogue between sports science and SportsHCI research.

5.1 Training Load Awareness Beyond Performance Data

Finding the "sweet spot" in training load [42] is highly personal and depends on how the athlete's body reacts to the training load. Therefore, sports science attributes great importance to TLM for improving athletes' performance to keep them physically and mentally healthy (as explained in Section 2.1). In parallel with this need, current sports trackers can measure various TLM-related data (as discussed in Section 2.2).

No doubt that tracking running related data provides runners with insights into their external (e.g., running distance and duration) and internal (e.g., heart rate) training load measures [31, 48, 50]. However, our study revealed that runners do not always show great interest in using this data in determining and adapting training load (Section 4.3). Still, although some runners are interested in using sports trackers' data, they found data-driven TLM limited, as it only allows using the data the technology can track. This is problematic, as TLM requires data beyond those performance metrics, such as runners' physiological (e.g., muscle and tissue damage [69]) and psychological adaptations to training load (e.g., disappointment about performance [20]).

Therefore, our results and the evidence from sports science research signal a discrepancy between what technology affords, what the runners want, and how training should be managed. We do not consider this a limitation but rather an opportunity for SportsHCI. It would be possible to provide a more holistic and personal TLM experience if sports trackers can acknowledge missing data and offer complementary advice to get a fuller picture of TLM. For instance, asking runners their Rating of Perceived Exertion (RPE) after a run and how "strong" they felt is a way to achieve that. This rating should also be combined with measured metrics and presented in a comprehensive manner. As much as identifying missing data, trackers could adapt to the runners' training load management needs, finetuning training load suggestions but not overwhelming them with irrelevant data since they give varying levels of importance to running-related metrics (as explained in Section 4.2.) In the next section, we reflect on how trackers can complement runners' subjective experiences with objective data and help them receive tailored TLM support.

5.2 Complementing Subjective Experience with Performance Metrics

As stated in Section 2, subjective rating of perceived effort (external load) [5] is a reliable and common way to quantify and assess internal load [17, 40]. According to our survey results, the runners did not deem this rating important in determining their training load. Conversely, interviews showed that runners use subjective assessments when managing their training load (e.g., P12, P15). These findings imply that runners tend to see quantified performance values as metrics for assessing training load (e.g., as heart rate), while they do not treat bodily signals as data sources. Yet, they use these signals to determine their exercise load (as in the case of self-directed training). Even though current sports trackers facilitate documenting ratings of perceived effort after running workouts, none of our participants explicitly mentioned using these

表8：跑步者的训练负荷管理实践及技术在这些实践中的作用

	训练负荷管理类型	
	指导式训练负荷管理	自主训练负荷管理
体育信息学的使用目的:	建立训练负荷管理能力 从多种来源学习	在训练负荷管理中保持自主性
确定和调整训练的来源 routines:	跑步相关数据 躯体信号 教练 规范训练计划	躯体信号
技术在训练负荷管理中的作用:	数据提供者 顾问	数据提供者 支持者

应被视为一个动态、演进的过程，并发现跑步者会随时间发展其训练负荷管理能力，逐渐变得更加自主。这一进展并不严格取决于跑步者是业余或精英运动员的身份；相反，它取决于有效利用数据。这包括持续反思个人经验以提升TLM熟练度。因此，我们的发现表明自我指导，或我们称之为“自主训练负荷管理”，

并非业余或精英运动员的专属领域。
相反，它随着训练负荷管理能力的提升而自然显现。
这种能力需通过长期与个人数据持续互动来培养，要求个体结合身体感觉进行解读。

我们的研究还揭示了跑步者知识体系间的摩擦
关于训练负荷、他们对追踪器的信任以及遵循追踪器训练负荷管理建议的情况（即数据对于管理训练负荷的重要性

或跑步者在经验与数据不符时对数据失去信任的倾向
如第4.4节所述）。此外，尽管当前的运动
如第4.4节所述）。此外，尽管当前的运动
体育人机交互研究在改进过程中面临的挑战与机遇

提升体育人机交互研究面临的挑战与机遇
训练负荷管理实践中的运动追踪。我们通过探讨
表现指标与主观体验之间的关系、
超越性能数据的训练负荷、以及跑步者
在管理自身训练时对追踪器的信任来展开讨论。最后，我们探讨了
运动科学与体育人机交互研究之间持续对话
可能带来的益处。

5.1 超越表现数据的训练负荷认知

找到训练负荷[42] 的“最佳点”具有高度个性化特征，取决于运动员的身体对训练负荷的反应。

因此，运动科学极为重视训练负荷管理（TLM）对提升运动员表现的作用，以保持其身体与心理健康（如第2.1节所述）。与此同时，

现有运动追踪器已能测量多种与训练负荷管理相关的数据（如第2.2节讨论）。

毫无疑问，追踪跑步相关数据能为跑者提供关于其外在（如跑步距离和持续时间）与内在（如心率）训练负荷测量[31, 48, 50]的洞察。

然而，我们的研究表明跑步者并不总是表现出强烈的兴趣来利用这些数据确定和调整训练负荷（第4.3节）。尽管如此，虽然部分跑者有兴趣利用
通过分析运动追踪器的数据，他们发现数据驱动的训练负荷管理存在局限性，因为它仅
允许使用该技术能追踪到的数据。这显然存在问题，
因为训练负荷管理需要超越那些表现指标的数据，例如
跑步者的生理状态（如肌肉和组织损伤[69]）以及
对训练负荷的心理适应（如对
表现的失望[20]）。

因此，我们的结果和运动科学研究的证据表明，技术提供的内容、跑步者的需求以及训练管理方式之间存在差异。

我们不认为这是一种局限，而是体育人机交互（SportsHCI）的一个机遇。
如果运动追踪器能够识别缺失数据并提供补充建议，
就有可能提供更全面、个性化的训练负荷管理（TLM）体验。
例如，询问跑步者的自觉用力程度评分（RPE），
以更完整地了解训练负荷管理。

跑步后以及他们感觉“有多强”是实现这一目标的一种方式。
这一评分还应与测量指标相结合，
并以全面的方式呈现。除了识别
缺失的数据，追踪器还可以适应跑步者的训练负荷
管理需求，微调训练负荷建议，但不会
用无关的数据让他们不堪重负，因为这些数据给出的信息各不相同。
对跑步相关指标的重要性层级（如
第4.2节所述）。在下一节中，我们将探讨追踪器如何
用客观数据补充跑步者的主观体验
并帮助他们获得定制化的TLM支持。

5.2 用表现指标补充主观体验 表现指标

如第2节所述，感知努力的主观评分（外在负荷）[5] 是一种可靠且常用的量化与评估方式

内部负荷[17, 40]。根据我们的调查结果，跑步者
并不认为该评分对确定他们的训练
负荷有重要意义。相反，访谈显示跑步者会使用主观
评估来管理训练负荷（例如P12、P15）。
这些发现意味着跑步者倾向于将量化表现值视为评估训练负荷的指标（例如心率

评分），但他们并不将身体信号视为数据源。然而，
他们会利用这些信号来确定运动负荷（如
自主训练的情况）。尽管当前的运动追踪器支持在跑步后记录感知努力评分

锻炼，我们的参与者中没有人明确提到使用这些

ratings effectively as part of TLM. Therefore, we think that making the perceived effort easier to be rated at the end of the workouts and eliminating the potential burden on the runners would help them integrate more subjective ratings into their TLM-related assessments.

A recurring theme in the findings was the distinction between measured and derived performance metrics. Runners trust trackers for measured metrics like distance and time, while there is scepticism about the technology's ability to perform the necessary integration in calculating derived metrics and training load. This scepticism could be related to runners' perceptions of trackers' limitations in accurately capturing the subjective aspects of their performance. Therefore, runners often prioritise self-development, self-awareness, and somatic cues in their training routines when they consider metrics derived from the trackers. In doing so, they tend to appreciate performance feedback in relative terms, considering their performance within their circumstances. For instance, runners do not acknowledge a decline in VO_2Max estimates associated with ageing but still perceive their performance as good. This preference for relative measures ties into runners' desire for a personalised understanding of their performance rather than only relying on objective and absolute values.

Training load can be perceived as a score accumulated and quantified from the acute-chronic load ratio (as described in [42]). However, our research reveals a notable emphasis on subjective experiences over quantified metrics, connecting our results to the importance of athlete resilience [see 22, 38]. Additionally, our findings suggest a disparity between scientific recommendations for TLM and how they *are* implemented in runners' TLM practices. Previous HCI studies on self-tracking acknowledge the importance of subjective experiences and suggest complementing quantified data with users' sensations. For example, Rapp and Tirabeni's [72] findings illustrate that amateur athletes trust the objectivity of the monitored parameters, while elite athletes trust their sensations in sports tracking more. However, our findings show that although none of our participants identified themselves as elite athletes, they also relied on their subjective sensations in TLM. Therefore, our studies highlight the complementary role of objective data to subjective experiences, not the other way around, as subjective experiences might be the guiding force in TLM rather than a mere afterthought. This stark contrast was apparent in runners' desire to be autonomous in managing their training workload and relying more on their bodily awareness. Hence, as we observe in the transition from Guided TLM to Self-directed TLM (Table 8), we suggest that future research explore how tracking technology can support the acquisition of competence in TLM while finding a way to remain in the background once such competence is achieved [as in the concept of unremarkable computing 87, 97].

5.3 Building Informed Trust in Trackers

Our results revealed that although many runners trust their trackers in calculating their training load, not all are willing to follow trackers' TLM-related recommendations. We found that trust in TLM recommendations from human coaches or self is higher than in recommendations from trackers. We see several similarities between these findings and ongoing sports technology discussions. Sports science research shows that experienced runners are inclined to trust the recommendations of human coaches more than an information system, and they tend to be more engaged in training when their training plans are developed and remotely supervised by a human [9]. Despite the evidence in their training data indicating a (potential) overload, runners are not always willing to change their training plan [34]. Being overenthusiastic about running might cause a runner to mistrust and ignore the evidence that indicates training overload, and they maintain (or even increase) training frequency. While most runners want to keep a healthy lifestyle, not complying with the evidence of inadequate training loads can cause running-related injuries and quitting running [49].

Combining the results of our study and evidence from sports science, we propose that the TLM support for experienced runners should be designed more like negotiation conversations rather than training suggestions [78]. Such support should not be perceived as coming from an authority but more from a negotiator whose task is to balance runners' beliefs and what the data tells. Examining human-agent collaborations in HCI, Cila [14] suggests that creating a balance in negotiation requires a joint commitment of humans and technological agents to the negotiation activity. Aligned with that, we think the runners should also be aware of the goals of the TLM negotiations. For instance, this negotiation can be done through the sports tracker interfaces and the dashboards that illustrate the benefits of keeping the training load within the sweet spot [42]. At the same time, the sports trackers should not overrule the autonomy of the runners in decision-making. Still, they should support microplanning and negotiations as a way of flexibility [26] in setting running-related goals.

For designing trackers to support runners' TLM, designers should be careful about how the training load is communicated. Since TLM is a crucial practice for runners' health, tracking technology should go beyond tracking and focus on runners' learning [28]. Mere compliance to TLM-related recommendations provided by the trackers would not support runners' learning practices (i.e., learning about the relationship between one's capacity and performance), nor learning how the internal and external factors influence training load. Trackers should communicate how training metrics and data jointly affect training load to support runners' learning. These findings also pave the path for AI-supported TLM applications that support balanced and individualised training load management practices.

Extending Rapp and Tirabeni's [72, 73] findings, our research indicates that non-elite runners also place significant trust in their bodily sensations and subjective feelings. Our findings suggest that SportsHCI should go beyond focusing on quantitative data and incorporate qualitative aspects, such as an athlete's feedback and perceived exertion levels. By doing so, these tools can provide a more comprehensive view of TLM, combining measured metrics with personal, subjective insights. This holistic approach acknowledges the complexity of human performance and the multifaceted nature of training, enabling runners of all levels to make more informed decisions tailored to their unique needs and experiences. In essence, SportsHCI should facilitate a balanced integration of data-driven insights and personal intuition in TLM, ensuring that runners can optimise their training in a scientifically informed and personally resonant way.

评分作为训练负荷管理的一部分。因此，我们认为
感知努力在锻炼结束时更易于评分
且消除跑步者可能承受的负担将有助于
他们整合更多主观评分到其训练负荷管理相关评估中

研究发现中一个反复出现的主题是测量指标与衍生表现指标之间的区别。跑步者信任追踪器提供的距离和时间等测量指标，但对技术能否在计算衍生指标和训练负荷时完成必要整合持怀疑态度。这种怀疑可能与跑步者对追踪器在准确捕捉其表现主观方面的局限性认知有关。因此，跑步者往往优先考虑自我发展，

当跑步者在训练计划中考虑来自追踪器的指标时，他们会结合自我意识和身体信号。通过这种方式，他们倾向于以相对的角度来评估表现反馈，即在自身情况下考量其表现。例如，

跑步者虽然不承认与年龄相关的最大摄氧量估计值下降，但仍认为自己的表现良好。

这种对相对指标的偏好与跑步者渴望个性化理解自身表现的需求相关，而非仅依赖客观和绝对的数值。

训练负荷可被视为从急性-慢性负荷比（如[42]所述）累积和量化的分数。然而，我们的研究揭示了对主观体验的显著重视超过量化指标，这一结果与运动员韧性的重要性相关联[参见22, 38]。此外，我们的发现表明科学建议的训练负荷管理与跑者的训练负荷管理实践之间存在差异。

先前关于自我追踪的人机交互研究承认主观体验的重要性，并建议用用户的感觉补充量化数据。例如，Rapp和Tirabeni的[72]发现表明，业余运动员信任监测参数的客观性，而精英运动员更信赖他们在运动追踪中的感觉。然而，我们的研究显示，尽管没有参与者自认为是精英运动员，

他们还依赖于自己在训练负荷管理中的主观感受。因此，我们的研究强调了客观数据对主观体验的补充作用，而非相反，因为主观体验可能是训练负荷管理中的主导力量，而非事后才考虑的因素。这种鲜明对比体现在跑步者希望自主管理训练负荷并更多依赖身体意识的愿望中。因此，正如我们从指导式训练负荷管理向自主训练负荷管理的过渡中所观察到的（表8），我们建议未来研究探索追踪技术如何支持训练负荷管理能力的获取，同时找到一种方式在能力达成后保持技术背景化[，如无感计算的概念87, 97]。

5.3 建立对追踪器的知情信任

我们的结果显示，尽管许多跑步者信任其追踪器计算的训练负荷，但并非所有人都愿意遵循追踪器提供的训练负荷管理相关建议。我们发现，跑步者对来自人类教练或自身的训练负荷管理建议的信任度高于对追踪器建议的信任。这些发现与当前运动技术领域的讨论存在多处相似之处。运动科学研究表明，经验丰富的跑者更倾向于信任人类教练的建议而非信息系统，且当训练计划由人类[9]制定并远程监督时，他们的训练参与度更高。即便训练数据表明存在（潜在）过度训练，跑者并不总是愿意调整训练计划[34]。对跑步的过度热情可能导致跑者质疑并忽视表明训练过度的证据，从而维持（甚至增加）训练频率。尽管多数跑者希望保持健康生活方式，

不遵循训练负荷不足的证据可能导致跑步相关伤害并放弃跑步[49]。

结合我们的研究结果与运动
科学证据，我们建议针对经验丰富的跑者的训练负荷管理支持
应设计得更像协商对话而非
训练建议[78]。此类支持不应被视为
来自权威机构，而应更像一位谈判者的角色，其任务是
平衡跑步者的信念与数据所揭示的真相。通过考察
人机交互领域中的人机协作，西拉[14] 指出建立
协商中的平衡需要人类与智能体形成共同承诺
技术代理参与协商活动。与此相一致的是，
我们认为跑步者也应当了解训练负荷管理（TLM）的目标
协商。例如，这种协商可以通过
运动追踪器界面和展示
将训练负荷保持在最佳点内益处的仪表盘来完成
[42]。同时，运动追踪器不应凌驾于
跑者在决策中的自主权。尽管如此，他们仍应
支持微观规划和协商，以此作为[26]灵活性的一种方式
设定跑步相关目标。

为设计支持跑者训练负荷管理的追踪器，设计师需谨慎考虑如何传达训练负荷信息。

由于训练负荷管理对跑者健康至关重要，追踪技术不应仅停留在追踪层面，而应聚焦于跑者的学习[28]。

单纯遵循追踪器提供的训练负荷管理相关建议，并不能支持跑者的学习实践（即了解个人能力与表现之间的关系），

也没有学习内部和外部因素如何影响训练负荷。追踪器应传达训练指标和数据如何共同影响训练负荷，以支持跑者的学习。这些发现还为人工智能支持的训练负荷管理应用铺平了道路，这些应用支持平衡且个性化的训练负荷管理实践。

扩展Rapp和Tirabeni的[72, 73] 发现，我们的研究
表明非精英跑者也高度信任他们的
身体感觉和主观感受。我们的发现建议
体育人机交互应超越对定量数据的关注，并
纳入定性方面，如运动员反馈和
感知用力水平。通过这种方式，这些工具能够提供
更全面的训练负荷管理视角，将测量指标
与个人主观见解相结合。这种整体方法承认人类表现的复杂性及训练的多面性，

使各级别跑步者都能根据
其独特需求和经验做出更明智的决策。
本质上，体育人机交互应促进
数据驱动见解和个人直觉在训练负荷管理中，确保
跑步者能以科学依据为基础优化他们的训练
个人共鸣的方式。

Aligned with prior research findings [18], we believe that fostering sensemaking of running-related data would empower runners to manage their training load effectively, especially guide data handling (e.g., seeing the patterns in TLM calculations) and interpretation (e.g., making sense of the patterns in TLM calculations). For example, while describing why the training load should be decreased or increased, the tracker can facilitate hiding or curating the collected data so that the runner observes the impacts of the adjusted training load. This way, any measurement errors in data could be explained, and the runner could be made aware that the collected data is not the absolute truth.

5.4 Towards an Integrated Training Load Management in SportsHCI

Given the results of our study and the challenges and opportunities identified above, we see several distinct future directions in sports informatics and SportsHCI. Better sports informatics systems need to be developed by considering insights from sports science and runners' current TLM practices. These should better fit the runners' training needs by supporting them through data in a manner that they can trust. Still, current HCI practices often focus on precise measurement and data representation, enhanced with human-experience-related factors. We think the SportsHCI can leverage more from sports data for TLM by considering the following directions.

Learning: The challenge of helping runners manage their training load is not solely about measuring, calculating, or estimating data. Instead, SportsHCI should strive for a holistic approach, providing athlete-centred reports that guide data handling and interpretation and help decision-making around training load and learning about TLM [13]. This approach goes beyond employing trackers to learn to regulate athletes' body reactions. It recognizes the importance of integrating subjective sensations and personal experience into TLM practices, even for non-elite athletes [72].

Trust: We found that runners are interested in receiving advice on their TLM but currently distrust the advice of trackers. They do not trust the accuracy of several derived metrics current trackers provide, some of which are essential for TLM (e.g., HR variability). If technology fails to calculate the training load, we need solutions to communicate relevant information to users in a way they can trust. As part of this, TLM support could be designed more like negotiation conversations balancing data with experiences rather than as authoritative suggestions [as suggested in 78].

Recording experiences: Current trackers already allow for subjective self-reporting (e.g., notes) of the workouts. Yet, firstly, not all relevant factors of experience are equally included, and secondly, such functions are not used very much in an integrated manner with the data. Future systems should expand on functions to record experience-related factors, like "muscle soreness", "disappointment in performance", or "feelings like a relaxing run". Furthermore, such data should also be reported more holistically in integration with the numbers rather than keeping them as a separate, unrelated measure. These alternative ways of recording experiences and data can benefit from prior research, such as the use of wearable e-textile displays to support group running [58] or the use of drones in mediating running groups [4] and supporting the well-being of runners [3].

Data vs. experience: Finally, we suggest that future sports trackers could benefit from fundamentally turning around the basic underlying paradigm of data versus experience: Rather than focusing on data and extending it with subjective experiences, they should put the subjective experience first, as the runners themselves do in practice, and then support the runner's experience and perception with data, insights and suggestions from the tracker's quantitative measurements.

It is also essential to recognize the evolving nature of data literacy as a key component in athletic training and decision-making. Data literacy extends beyond mere comprehension of data; it encompasses the ability to critically evaluate and effectively utilise data in everyday practice [45], in college sports [16] and recreational running [67]. This aspect is particularly salient in our study on TLM, where we observe that as runners gain experience, they develop a nuanced form of data literacy. This progression is about accumulating knowledge and cultivating a critical perspective towards the data they encounter. Runners learn to question the relevance, accuracy, and applicability of TLM-related data, which is a crucial step in making informed decisions about their training plans.

TLM as a promising field of research for SportsHCI: We think our results can also be useful for other sports. Our research in running, a sport where athletes extensively self-track and manage training loads to enhance performance, has revealed insights with broad applications across various sports. This approach is particularly relevant for sports with high injury incidence, such as cycling, swimming, triathlon, and multisport disciplines, where athletes can benefit from using personal trackers to monitor and adjust their training loads. Even in team sports like soccer, emerging technologies like smart socks[8] and shin guards[9] are beginning to allow similar data-driven training optimisations. These advancements highlight the importance of incorporating athletes' feedback into technology design, ensuring that devices offer practical, user-friendly advice and interpretations. As more sports adopt these innovative tracking tools, the findings gathered from the running context can guide their development for more personalized and effective training methods across diverse sporting disciplines.

Cross-disciplinary collaboration between sports science, HCI and interaction design could help advance this nascent research area. One potential direction is conducting further integration of the perspective of these fields. For instance, our results showed the mismatches between runners' expectations from sports tracking, tracking capabilities of technology (e.g., tracking heart rate) and how technology utilises/communicates data (e.g., making training suggestions based on heart rate variability). Uncovering the reasons for these mismatches together with sports scientists and addressing them with better interaction design requires explicating the roles users, technology, and science could play in TLM.

6 CONCLUSIONS

In this paper, we showed the importance of training load management for the well-being of runners and illustrated how they

[8]https://www.danusports.com/ (Retrieved on 28 November 2023)
[9]https://humanox.com/en/hx50-shin-guard/ (Retrieved on 28 November 2023)

与先前研究发现[18], 一致，我们认为促进跑步相关数据的意义建构将赋能跑步者

有效管理他们的训练负荷，特别是指导数据
处理（例如，观察TLM计算中的模式）和解释（例如，理解TLM计算中的模式）。

例如，在描述为什么训练负荷应该
减少或增加时，追踪器可以促进隐藏或整理
收集的数据，以便跑步者观察调整后的训练负荷所产生的影响。
通过这种方式，可以解释数据中的任何测量误差，
并让跑步者意识到所收集的数据并非绝对真理。
收集的数据并非绝对真理。

5.4 迈向体育人机交互中集成的训练负荷管理

基于我们的研究结果以及上述挑战与机遇，我们在体育信息学与体育人机交互领域看到了几个明确的未来发展方向。更好的体育信息系统需要结合运动科学的洞察和跑步者当前的训练负荷管理实践来开发。这些系统应通过以可信赖的方式提供数据支持，更好地满足跑步者的训练需求。然而，当前的人机交互实践往往侧重于精确测量和数据表示，并辅以与人类经验相关的因素。我们认为，体育人机交互可以通过以下方向更充分地利用运动数据进行训练负荷管理。

学习：帮助跑步者管理训练负荷的挑战不仅在于测量、计算或估算数据。体育人机交互应追求一种整体方法，提供以运动员为中心的报告，指导数据处理和解读，并协助围绕训练负荷和训练负荷管理[13]的决策学习。这种方法超越了使用追踪器来学习调节运动员身体反应的范畴，它认识到将主观感受和个人经验融入训练负荷管理实践的重要性，即使对非精英运动员[72]也是如此。

信任：我们发现跑步者有兴趣接收关于
他们训练负荷管理的建议，但目前不信任追踪器提供的建议。他们
不信任当前追踪器提供的几种衍生指标的准确性，
其中一些对训练负荷管理至关重要（例如心率变异性）。
如果技术无法计算训练负荷，我们需要解决方案
以用户能够信任的方式传达相关信息
信任。作为其中的一部分，训练负荷管理支持可以设计得更像
协商对话，平衡数据与经验，而非
作为权威建议[如78]中所建议的那样。

记录经验：当前的追踪器已经允许对锻炼进行主观自我报告（例如笔记）。然而，首先，并非所有相关经验因素都被平等地包含在内，其次，

这些功能并未与数据紧密结合使用。未来的系统应扩展记录经验相关因素的功能，如“肌肉酸痛”、“表现失望”或“放松跑步的感觉”。此外，

此类数据还应更全面地与数字整合报告，而非将其作为独立且无关的度量标准。这些记录经验和数据的替代方法可从先前研究中获益，例如使用可穿戴电子纺织品显示器来支持团体跑步[58] 或使用无人机

在调解跑步团体[4] 和支持跑步者的福祉[3]方面。

数据与体验：最后，我们建议未来的运动追踪器可以从根本上扭转数据与体验的基本范式：不应以数据为核心并辅以主观体验，而应像跑者实际所做的那样，将主观体验置于首位，再通过追踪器的定量测量提供数据、洞察与建议来支持跑者的体验与感知。

同样关键的是要认识到数据素养作为运动训练与决策核心要素的演进特性。数据素养不仅限于对数据的理解，更包含在日常大学体育[45], 和休闲跑步[16] [67]实践中批判性评估并有效运用数据的能力。这一特性在我们关于训练负荷管理（TLM）的研究中尤为突出，

我们观察到随着跑者经验积累，他们会发展出一种精细的数据素养。这种进步不仅关乎知识的积累，更在于培养对所遇数据的批判视角。跑者学会质疑数据的相关性，

与训练负荷管理相关的数据的准确性及适用性，这是制定关于训练计划的明智决策的关键一步。

训练负荷管理作为体育人机交互领域一个有前景的研究方向：我们认为我们的
结果对其他运动项目也有参考价值。我们在跑步这一运动中的研究，
一项运动员广泛自我追踪并管理训练负荷以提升表现的运动，揭示了具有广泛
适用性的洞察，可应用于多种运动项目。这一方法尤其
这种方法尤其适用于多种体育项目。
对于受伤率较高的运动项目尤为重要，例如自行车运动、
游泳、铁人三项和多项运动，这些项目的运动员
可通过使用个人追踪器来监测并调整
其训练负荷。即便在足球等团队运动中，新兴
技术如智能袜子8和护腿板9已开始
实现类似的数据驱动训练优化。这些进步凸显了整合运动员反馈

融入技术设计，确保设备提供实用、用户友好的建议和解读。随着更多运动项目采用这些

创新追踪工具，从跑步情境中收集的发现
可以指导其开发更个性化和
有效的训练方法，适用于多样化的运动项目。

运动科学、人机交互
与交互设计之间的跨学科合作有助于推动这一新兴研究领域的发展。
领域。一个潜在方向是进一步整合
这些领域的视角。例如，我们的结果显示
跑步者的期望与运动追踪之间的不匹配，
技术的追踪能力（如追踪心率）以及
技术如何利用/传达数据（例如根据
心率变异性提供训练建议）。揭示这些原因
与运动科学家共同解决这些不匹配问题，并通过
更好的交互设计来处理它们，需要明确
用户、技术和科学在训练负荷管理（TLM）中可能扮演的角色。

6 结论

本文中，我们揭示了训练负荷管理对跑步者健康的重要性，并阐述了他们

8https://www.danusports.com/（检索于2023年11月28日） 9https://humanox.com/en/hx50-shin-guard/（检索于2023年11月28日）

use sports trackers in TLM practices. Despite its significance in athletes' well-being, and although the current trackers can record much of the necessary data for TLM, HCI literature has largely overlooked TLM till now. Our findings address this gap by providing a novel lens on how the users of sports tracking technology should be supported to help them make decisions related to training load. Accordingly, by closely looking into runners' TLM practices, we unravelled the dynamic nature of TLM, encompassing runners' transition from Guided TLM to Self-Directed TLM by reflecting on their data and running experiences. We have uncovered varying levels of interest in quantifying and utilising running-related metrics for TLM and a desire to personalise training programs according to a multitude of factors beyond performance metrics. We have also highlighted a discrepancy between what sports science literature suggests as the best practice for TLM, what aspects of training load trackers can quantify and what aspects of training load runners are interested in tracking.

Overall, our findings signal a new line of sports trackers prioritising the subjective experience and bodily signals over data provided by the technology, where the latter is only used to complement the former. We conclude that developing such trackers would be only possible with an ongoing dialogue between SportsHCI and Sports Science domains, involving users as experts in their lived experiences. All in all, this paper is an attempt to initiate such a dialogue.

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如何将运动追踪器应用于训练负荷管理实践。尽管其对运动员福祉至关重要，且现有追踪器能记录大部分训练负荷管理所需数据，人机交互文献迄今却鲜少关注该领域。我们的发现通过提供全新视角——关于如何支持运动追踪技术用户做出训练负荷相关决策——填补了这一空白。为此，我们深入研究了跑者的训练负荷管理实践，

我们揭示了训练负荷管理（TLM）的动态本质，包括跑步者通过反思自身数据和跑步体验，从指导式训练负荷管理过渡到自主训练负荷管理的过程。我们发现跑步者对量化并利用跑步相关指标进行TLM的兴趣程度不一，且渴望根据表现指标之外的多种因素个性化训练计划。我们还指出运动科学文献建议的TLM最佳实践、训练负荷追踪器可量化的方面，以及跑步者感兴趣的追踪内容之间存在差异。

总体而言，我们的发现预示着一类新型运动追踪器的诞生——它们将主观体验和身体信号置于技术提供的数据之上，后者仅作为前者的补充。我们得出结论：只有通过体育人机交互（SportsHCI）与运动科学领域持续对话，并将用户作为其生活经验专家纳入其中，才可能开发出此类追踪器。本文正是开启这一对话的尝试。

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