Maximising the Usefulness of Wearable Data for Athletes

Saaz Kaur Sahdra
The University of Sydney
Sydney, NSW, Australia

Grant Duthie
Australian Catholic University
Sydney, NSW, Australia

Judy Kay
The University of Sydney
Sydney, NSW, Australia

Kalina Yacef
The University of Sydney
Sydney, NSW, Australia

ABSTRACT

Athletes can and do use wearables and personal devices to track multiple aspects of personal information about their performance, but it is currently difficult for them to gain an integrated and useful picture of their long-term information. We designed a questionnaire to investigate whether athletes value and track four important factors (physical health, mental health, nutrition, and sleep) in relation to their performance using wearables and current athlete management systems. Sixteen athletes from various sports completed the questionnaire. Key results show the mismatch between perceived value versus actual nutrition, sleep, and mental health tracking but consistency on physical health. There also seems to be a divide on the perceived usefulness of athlete management systems. These results point to challenges for collecting and interpreting data that athletes want and also inform the design of athlete management systems, especially those that integrate both self-reported and wearable data.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**; • **Applied computing → Health informatics**.

KEYWORDS

wearables, athletes, personal informatics, user needs, sportsHCI

ACM Reference Format:
Saaz Kaur Sahdra, Grant Duthie, Judy Kay, and Kalina Yacef. 2024. Maximising the Usefulness of Wearable Data for Athletes. In *Companion of the 2024 ACM International Joint Conference on Pervasive and Ubiquitous Computing Pervasive and Ubiquitous Computing (UbiComp Companion '24), October 5–9, 2024, Melbourne, VIC, Australia.* ACM, Melbourne, Australia, 6 pages. https://doi.org/10.1145/3675094.3677600

1 INTRODUCTION

Athletes who use wearables and personal devices often aim to collect and reflect on their personal information about their performance. Based on long-term personal information records, athletes and coaches decide to continue or change behaviour to improve performance. However, user experience problems limit the effectiveness of systems intended to help people interpret personal information from sensor technologies and easy-to-use journals to change behaviour [9, 25]. This study aims to establish the requirements for future research on athlete management frameworks that integrate diverse forms of personal data to provide valuable insights about athlete performance.

Sports science literature has identified over twenty relevant variables, collected from wearables and self-reported measures, that affect an athlete's development and performance, [2–6, 23, 28]. We have grouped these variables into four larger categories: physical health, mental health, sleep, and nutrition (hereby referred to as four "factors"). These factors do not include static or external environmental factors, but they are the main simplified groups of variables used in the assessment of athletes. Analysing multiple factors together can provide a data-driven holistic understanding of an individual's talent development and sporting performance [14, 30, 42]. But to gather personalised insights of multiple factors on an individual athlete, time series data is needed (N-of-1 data), which calls for long-term multi-variate tracking [10]. To our knowledge, these four factors have not been analysed together quantitatively to understand how they can be combined for a holistic picture of factors affecting an athlete's performance.

To address the research-practice gap, we aimed to answer the following research questions: **(RQ1)** Which factors do athletes perceive as important for their performance? **(RQ2)** Which factors do athletes actually monitor to improve their performance? **(RQ3)** Which factors do athletes find useful to monitor using current athlete management system platforms?

2 RELATED WORK

Many theories underpin Personal Informatics, a human-computer interaction research area that aims to gain insights to harnessing long-term tracking data. Epstein et al. [12] builds upon the Li et al. [25] linear model and proposed a cyclic model with three main stages: configuration, data capture, and feedback. Like Li et al. [25], Epstein et al. [12] identify how barriers cascade over different stages and that systems should be user-driven and multifaceted. But the Epstein et al. [12] model adds stages for goal-orientated trackers and the types of motivations for deciding to track. The model also accounts for 'lapsing' and 'resuming' to understand micro and macro gaps that occur in long-term tracking data [11]. An athlete might decide to temporarily stop using their tracking device or filling out their journal. Why these gaps occur depends on the individual's context, but the literature has identified that if automation is limited, long-term tracking can increase the cost of tracking

UbiComp Companion '24, October 5–9, 2024, Melbourne, VIC, Australia

ACM ISBN 979-8-4007-1058-2/24/10
https://doi.org/10.1145/3675094.3677600

effort or maintenance, compromising the data quality [7, 10, 11, 24]. Specific to athletes is a focus on tracking for sport-specific goals [36]. Overall, key challenges for long-term personal information tracking are balancing the effort of tracking with quality of data and interpreting the data with contextual information [11].

Use of rich collections of diverse tracking data for individuals and groups has been explored in multiple disciplines, including sports science, health science, and personal informatics. Studies combining physical health markers and nutrition for athlete training and performance include Mata et al. [27], Donciu et al. [8], Hakkila et al. [16], Heather et al. [18], and Martin et al. [26]. Others linked physical health and psychological markers in relation to athlete identity and performance such as Ng and Ryba [33], Rapp and Tirabeni [38], Abdullah et al. [1], Heather et al. [18], and Van Ryswyk et al. [45]. Generally, previous work has explored ways to enable coaches and athletes to reflect on one or two of the four factors, typically over a short term.

Although Smyth et al. [42] mention how all four factors and environmental context can affect a recreational runner's performance, they used only physical activity from Strava [19] for machine learning algorithms driving recommendations. Similarly, the runners' recommender system by Donciu et al. [8] used physical activity data with nutrition data to personalise recommendations for pre- and post-running nutrition. Neither recommender system collected data on other measures, such as sleep or mental state. Sports recommender systems that do analyse at least two of the four factors often do not support bundled recommendations [15]. For example, food recommenders do not also guide training sessions and sleep.

Data mining in sport science for human activity recognition (HAR) has been concentrated within computer vision, with some multimodal work combining video and multiple wearables [37, 46, 48]. These approaches primarily apply deep learning models like CNN. However these methods can be very costly and need large amounts of labelled data, which can be difficult to collect in health domains [46]. Data synchronisation and high-dimensional processing issues make it difficult to process self-collected multimodal data [48] and current conceptual frameworks that aim to build discovery pipelines (i.e., Phatak et al.[37]), fail to account for temporal changes in user motivations during data collection (i.e., Epstein et al. model. [12]). Data collection frameworks from Personal Informatics and Sport Science need to be bridged.

Despite the consensus that multiple factors and processes affect an individual's health and performance, both computer science and sports science literature have not done this. Even with many wearables, easy-to-use self-reported journals, and platforms that combine data from various sources [28, 29, 35, 41, 49], their integrated use has not been realised for all four factors.

3 STUDY DESIGN

Are athletes unsatisfied with current systems because they do not meet personalisation needs, or do athletes simply not see value in tracking all four factors to improve their performance? To answer our research questions and discover whether athletes' tracking perceptions and behaviours align, we designed a questionnaire[1]. This was administered in Qualtrics. We recruited athletes via Australian university sports clubs, social media, and sports newsletters.[2]

Since prior research has identified differences in wearable use between amateur and elite athletes, the survey first asked demographic, sport, and training-specific questions to classify their level of "eliteness" [38, 39, 44]. Athletes were then asked to rate the importance of tracking each factors for their performance (RQ1) and about their use of wearables (RQ2). Participants were asked about the wearables they use, how often they use them, how long they have been using them, and why they use or stopped using them.

Current athlete monitoring tools focus on the coach's perspective [32, 40, 43]. Since these tools collect athletes' data, from athletes, we asked athlete participants about the usefulness of the AMS [34] (an athlete management system created by the Australian Institute of Sport) to their success as an athlete (RQ3). The AMS aims to capture, analyse, and visualise "data from a variety of sources including athlete entered questionnaires, automated integration of wellbeing and monitoring tools, and purpose-built applications" [34].

Participants were invited to provide brief explanations throughout the survey to help identify potential challenges they face regarding tracking, interpretation, and data sharing concerns. For example, RQ1 and RQ3 were presented as a matrix with a Likert scale and a comment box next to each scale. Participants were asked to briefly explain their Likert scale choice in the box.

4 RESULTS

The questionnaire was completed by 16 athletes (12 male, 4 female, age range = 21-41+, median age = 38). They are from diverse sports (N=12), and most reside in Australia (N=14). Over 80% use a wearable tracker almost every day, most for over 4 years (max=15, min=1.3). About half (N=9) use a Garmin Watch or Apple Watch. Other wearables reported include Fitbit, Oura Ring, Polar Watch, Wahoo, and Whoop. Just one did not use a wearable tracker, but is open to using one in the future.

Figure 1 shows the importance ratings for each of the four factors to track. These results address RQ1. Strikingly, over 60% of athletes saw each of the four factors as at least important. Notably, this was over 90% (15 out of 16 athletes) for sleep. For physical health, this was over 80% (13 out of 16 athletes). Only 3 of the athletes rated mental health as unimportant and only 1 that for nutrition.

Figure 2 shows which of the factors these athletes actually track. These results address RQ2. Although around two-thirds of respondents do track all four factors, physical health was the only pillar all athletes track. For physical health, 6.2% of these athletes only tracked their physical health outside of training, 18.8% of athletes only tracked their physical health during training, and 75% tracked physical health both during and outside training sessions/seasons. Almost a third of athletes did not track nutrition at all, and a quarter did not track mental health.

Comparing Figure 1 and Figure 2, we can see a mismatch between the perceived importance and actual tracking of nutrition, mental health, and sleep. Only the physical health had close alignment between perceived value and tracking behavior.

Figure 3 shows feedback from the athletes who use the AMS (N=8) when asked how useful they believe the AMS is in tracking

[1]Institutional Ethics Committee - HREC Approval No.: 2023/710. This research is supported by an Australian Government Research Training Program (RTP) Scholarship.

[2]A copy of the questionnaire is available online here.

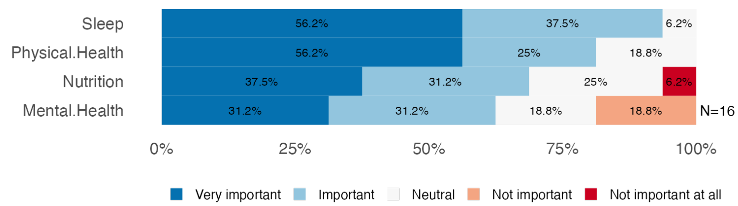

Figure 1: Questionnaire responses to: "As an athlete, how important is it to track these factors in relation to your performance?"

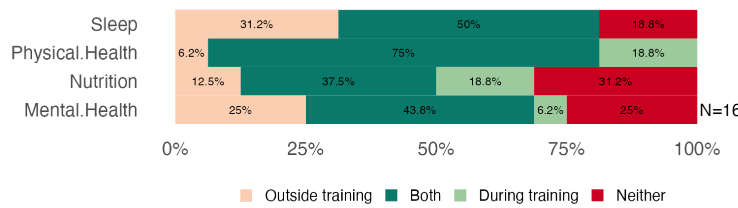

Figure 2: Questionnaire responses to: "Have you or your coach tracked any of these factors?"

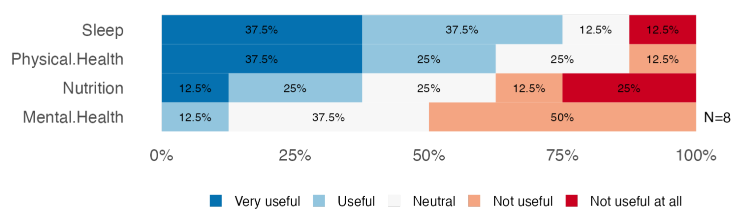

Figure 3: Questionnaire responses to: "How useful do you think the Athlete Management System (AMS) is to your success as an athlete? Very briefly explain why you feel that way."

the four factors for their success as an athlete. These results address RQ3. Respondents were divided about the usefulness of the AMS. Although 5 out of the 8 athletes view the AMS as useful for sleep and physical health, only 1 athlete found it useful for mental health and 3 found it useful for nutrition. Table 1 provides examples of the explanations for the ratings summarised in Figure 3. These indicate the diverse views and experiences of these participants.

5 DISCUSSION

Athletes who answered the questionnaire overwhelmingly supported the notion that all four factors are important for their performance (see Figure 1). This finding aligns with the broader sports science literature [4]. The athletes may be well-educated with sports science theories and studies, may have coaches who are well-read in the discipline, or may have experienced first hand how each pillar affects their performance. Nevertheless, some of these athletes are not tracking every pillar (see Figure 2) even if they believe it is important to track and are unsatisfied with current athlete management systems (see Figure 3).

5.1 Physical Health

Sports is heavily focused on the physical body. Unsurprisingly, most wearable technologies developed in the industry have focused on physical health markers such as heart rate [28]. Athletes from the questionnaire find physical health a very important factor to consider tracking in relation to performance which seemingly translated to all respondents tracking physical health. In fact, majority of the athletes track physical health both during and outside of training. The intense focus within engineering and health industries on improving such technologies that measure physical health, such as their non-intrusivity and automation of data collection, might have had an impact in physical health being most tracked out of all of the factors. Situating these technologies within the Epstein et al. [12] model, such non-intrusivity and automation reduces lapsing and enables continuity of tracking and acting. Nevertheless, there is still room for improvement–a survey respondent mentioned that although the AMS is useful in relation to an athlete's physical health success, they "don't think there is a platform out there which monitors [physical health] well enough." Many current sports recommender systems lack integration of sport-specific goals and real-time feedback, which may be shortcomings relevant to monitoring physical health [15, 36].

5.2 Sleep

Users often seek greater personalisation and tailored feedback to understand and change behaviours [33, 39], which could explain the disconnect between questionnaire respondents feeling sleep is an important variable and not tracking it despite already having the technology to do so. It is possible that sleep analysis feedback is not presented in a way users can easily digest and understand. A survey respondent also expressed concerns about accuracy and validity of sleep analysis of current platforms, "I'm not sure of the accuracy of the current platforms that rate sleep quality and track sleep time." Athletes, especially elites, are disciplined characters and although they believe sleep is imperative for their performance, tracking sleep does not feel necessary [38, 39]. Taking into consideration the types of motivations outlined in the Epstein et al. [12] model, an athlete's motivation for deciding to track can change over time, depending on the broader context. Athletes might find it useful to track sleep when they are faced with jet-lag challenges during international competitions [20]. Tracking sleep might feel necessary at different stages of an athlete's journey and future systems should address uncertainty concerns associated with sleep analysis results. We suspect that future systems also need to take into consideration how

Table 1: Selected comments explaining the rating for "How useful do you think the Athlete Management System (AMS) is to your success as an athlete?"

Physical Health Very Useful / Useful: *"I can measure how I'm performing over the long term", "Helping to maintain motivation", "Good for fast bowlers to manage load and reduce injury", "This is key to monitoring improvement, but I don't think there is a platform out there which monitors it well enough", "My whole training is based off HR. Without being able to access that data I would find it very hard to train the way I do."* Not Useful / Not useful at all: *"Experience tells me what to watch out for"*
Mental Health Very Useful / Useful: *"My mental health is very much linked to feeling physically fit", "For athletes who are more challenged with mental health, tracking success against mental health conditions may provide them valuable insights"* Not Useful / Not useful at all: *"Not enough truth from athletes to make relevant", "Experience tells me what to watch out for stressors impacting performance", "Its not something that I really track, I just say when I feel that way"*
Nutrition Very Useful / Useful: *"I think it could assist, particularly in tracking if there is a performance issue. But for me, like many athletes, the existing methods of data input are too onerous or too variable. To understand the full picture of all nutrition should be tracked 100% of the time, not just during and post exercise", "Impacting performance and recovery. Making sure the right foods are being consumed"* Not Useful / Not useful at all: *"Relies too much manual input", "Again, I don't track and dont think I ever will again due to prior issues"*
Sleep Very Useful / Useful: *"It is tracked but only because I wear my watch all the time. I know if I have had a bad nights sleep or if I'm not getting enough sleep based off how I feel. I don't need/use the data there really", "Helps to adjust training load as needed", "Longitudinal data very important can predict and foresee injuries", "I think sleep tracking is valuable for monitoring performance. But I'm not sure of the accuracy of the current platforms that rate sleep quality and track sleep time"* Not Useful / Not useful at all: *"No data tracking"*

motivation for deciding to track can change over time–motivations during off season might be out of curiosity or instrumental, whereas during pre-season they might be because of behaviour change or domain specific goals, such as travel effects. These changes in motivations change the manner in which data should be reflected on to avoid lapsing.

5.3 Nutrition

Most respondents found nutrition to be an important factor to track in relation to athlete performance, however over 30% of respondents do not track nutrition at all. Nutrition is a difficult variable to measure and collect data on long term. Commercial apps such as MyFitnessPal and researchers such as Donciu et al. [8], Mata et al. [27], and Wilson-Barnes et al. [47] have worked on designing platforms that can track and recommend nutrition for user needs. However, validity and accuracy issues around self-reported nutrition diaries regarding caloric counts, intake time, macro/micro-nutrient counts are prevalent [13, 17, 21, 26, 27]. Questionnaire respondents found nutrition tracking, "too much manual input" and that "the existing methods of data input are too onerous or too variable" even if they found it useful to track. Unlike sleep, these athletes are less concerned with validity or accuracy of nutrition tracking, rather the mismatch between perceived importance of nutrition and actual tracking seems to be due to the time consuming nature of nutrition diaries. Taking into consideration the Epstein et al. [12] model, to avoid lapsing, nutrition tracking needs to minimise manual input to reduce user burden.

5.4 Mental Health

Like nutrition, most respondents found mental health as an important pillar, however a quarter of the athletes did not track its effects on their performance. Mental health is not easily tracked long-term and pattern identification and interventions need to be personalised to the individual and interpersonal contexts [31]. There are many studies about tracking mental health in the personal informatics literature, such as Rapp and Tirabeni et al. [39], Murnane et al.[31], and Kim et al. [22]. However, current systems used by athletes in Australia, such as the AMS, seem to lack explainability [22] and fail to create trust with its users (see Table 1 - Mental Health). A questionnaire respondent mentioned there is "not enough truth from athletes" and another mentioned that the question on the AMS was a simple question asking whether you need help or not. The AMS seems to lack nuance and half of the respondents found the AMS was not useful for tracking their mental health in relation to their success as an athlete (see Figure 3). Although sport psychology and personal informatics related to mental health are extensive fields of research and athletes clearly understand its importance towards their performance, systems are competing with individual intuition. Future studies should focus on creating systems with greater explainability surrounding mental health tracking to highlight where intuition might fail.

6 CONCLUSION

There is some to much dissatisfaction with current platforms in regards to all four factors and there is a need to investigate how we can improve the data collection and long-term monitoring of the four factors, especially nutrition, mental health and sleep. Overall, it seems the greater reliance on self-report measures, the less a factor is tracked. Although the results support the notion that there is a gap between theory and practice around tracking and monitoring tools, this study is limited by its lack of sample diversity, older-male athlete bias, and the potential bias of self-reporting. Nevertheless, the mismatch seen between perceived importance and actual tracking of the four factors in this study contributes towards establishing parameters that need to be considered when creating athlete data management platforms. Future studies could extend this study by collecting data from more athletes to discover greater qualitative data on how dissatisfaction with current platforms can be addressed. Future research might also like to focus on improving the communication of methods and visualisations of data to address the lack of trust and reliance on experience, which might encourage athletes to explore their data to discover new patterns and possible ways to improve their performance.

REFERENCES

[1] Mohamad Razali Abdullah, Ahmad Bisyri Husin Musawi Maliki, Rabiu Muazu Musa, Norlaila Azura Kosni, Hafizan Juahir, and Mainul Haque. 2016. Multi-Hierarchical Pattern Recognition of Athlete's Relative Performance as A Criterion for Predicting Potential Athletes. *Journal of Young Pharmacists* 8, 4 (Aug. 2016), 463–470. https://doi.org/10.5530/jyp.2016.4.24

[2] Rachel Arnold, David Fletcher, and Robbie Anderson. 2015. Leadership and Management in Elite Sport: Factors Perceived to Influence Performance. *International Journal of Sports Science & Coaching* 10, 2-3 (June 2015), 285–304. https://doi.org/10.1260/1747-9541.10.2-3.285

[3] Chris Bailey. 2019. Longitudinal Monitoring of Athletes: Statistical Issues and Best Practices. *Journal of Science in Sport and Exercise* 1, 3 (Nov. 2019), 217–227. https://doi.org/10.1007/s42978-019-00042-4

[4] Joseph Baker, Stephen Cobley, and Jörg Schorer. 2020. *Talent Identification and Development in Sport: International Perspectives* (2 ed.). Routledge. https://doi.org/10.4324/9781003049111

[5] Theodoros Bampouras, Colum Cronin, and Paul K. Miller. 2012. Performance analytic processes in elite sport practice: an exploratory investigation of the perspectives of a sport scientist, coach and athlete. *International Journal of Performance Analysis in Sport* 12, 2 (2012), 468–483.

[6] Tudor O. Bompa, James Hoffmann, and Scott Howell. 2019. *Integrated periodization in sports training & athletic development: combining training methodology, sports psychology, and nutrition to optimize performance.* Meyer & Meyer Sport, Maidenhead (UK).

[7] Ludovico Boratto, Salvatore Carta, Fabrizio Mulas, and Paolo Pilloni. 2017. An e-coaching ecosystem: design and effectiveness analysis of the engagement of remote coaching on athletes. *Personal and Ubiquitous Computing* 21, 4 (Aug. 2017), 689–704. https://doi.org/10.1007/s00779-017-1026-0

[8] Mihnea Donciu, Madalina Ionita, Mihai Dascalu, and Stefan Trausan-Matu. 2011. The Runner – Recommender System of Workout and Nutrition for Runners. In *2011 13th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing*. IEEE, Timisoara, TBD, Romania, 230–238. https://doi.org/10.1109/SYNASC.2011.18

[9] Don Samitha Elvitigala, Armağan Karahanoğlu, Andrii Matviienko, Laia Turmo Vidal, Dees Postma, Michael D Jones, Maria F. Montoya, Daniel Harrison, Lars Elbæk, Florian Daiber, Lisa Anneke Burr, Rakesh Patibanda, Paolo Buono, Perttu Hämäläinen, Robby Van Delden, Regina Bernhaupt, Xipei Ren, Vincent Van Rheden, Fabio Zambetta, Elise Van Den Hoven, Carine Lallemand, Dennis Reidsma, and Florian 'Floyd' Mueller. 2024. Grand Challenges in SportsHCI. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. ACM, Honolulu HI USA, 1–20. https://doi.org/10.1145/3613904.3642050

[10] Daniel A. Epstein, Clara Caldeira, Mayara Costa Figueiredo, Xi Lu, Lucas M. Silva, Lucretia Williams, Jong Ho Lee, Qingyang Li, Simran Ahuja, Qiuer Chen, Payam Dowlatyari, Craig Hilby, Sazeda Sultana, Elizabeth V. Eikey, and Yunan Chen. 2020. Mapping and Taking Stock of the Personal Informatics Literature. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 4, 4 (Dec. 2020), 1–38. https://doi.org/10.1145/3432231

[11] Daniel A. Epstein, Parisa Eslambolchilar, Judy Kay, Jochen Meyer, and Sean A. Munson. 2021. Opportunities and Challenges for Long-Term Tracking. In *Advances in Longitudinal HCI Research*, Evangelos Karapanos, Jens Gerken, Jesper Kjeldskov, and Mikael B. Skov (Eds.). Springer International Publishing, Cham, 177–206. https://doi.org/10.1007/978-3-030-67322-2_9 Series Title: Human–Computer Interaction Series.

[12] Daniel A. Epstein, An Ping, James Fogarty, and Sean A. Munson. 2015. A lived informatics model of personal informatics. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, Osaka Japan, 731–742. https://doi.org/10.1145/2750858.2804250

[13] Juliana Exel and Peter Dabnichki. 2024. Precision Sports Science: What Is Next for Data Analytics for Athlete Performance and Well-Being Optimization? *Applied Sciences* 14, 8 (April 2024), 3361. https://doi.org/10.3390/app14083361

[14] J. Fahey-Gilmour, B. Dawson, P. Peeling, J. Heasman, and B. Rogalski. 2019. Multifactorial analysis of factors influencing elite australian football match outcomes: a machine learning approach. *International Journal of Computer Science in Sport* 18, 3 (Dec. 2019), 100–124. https://doi.org/10.2478/ijcss-2019-0020

[15] Alexander Felfernig, Manfred Wundara, Thi Ngoc Trang Tran, Viet-Man Le, Sebastian Lubos, and Seda Polat-Erdeniz. 2023. Sports Recommender Systems: Overview and Research Issues. https://doi.org/10.21203/rs.3.rs-3710874/v1

[16] Jonna Hakkila, Mira Alhonsuo, Lasse Virtanen, Juho Rantakari, Ashley Colley, and Timo Koivumaki. 2016. MyData Approach for Personal Health – A Service Design Case for Young Athletes. In *2016 49th Hawaii International Conference on System Sciences (HICSS)*. IEEE, Koloa, HI, USA, 3493–3502. https://doi.org/10.1109/HICSS.2016.436

[17] Shona L. Halson. 2014. Sleep in Elite Athletes and Nutritional Interventions to Enhance Sleep. *Sports Medicine* 44, S1 (May 2014), 13–23. https://doi.org/10.1007/s40279-014-0147-0

[18] Alison K. Heather, Holly Thorpe, Megan Ogilvie, Stacy T. Sims, Sarah Beable, Stella Milsom, Katherine L. Schofield, Lynne Coleman, and Bruce Hamilton. 2021. Biological and Socio-Cultural Factors Have the Potential to Influence the Health and Performance of Elite Female Athletes: A Cross Sectional Survey of 219 Elite Female Athletes in Aotearoa New Zealand. *Frontiers in Sports and Active Living* 3 (Feb. 2021), 601420. https://doi.org/10.3389/fspor.2021.601420

[19] Strava Inc. 2024. Strava. https://www.strava.com/features

[20] Dina C(Christa) Janse Van Rensburg, Audrey Jansen Van Rensburg, Peter Fowler, Hugh Fullagar, David Stevens, Shona Halson, Amy Bender, Grace Vincent, Amanda Claassen-Smithers, Ian Dunican, Gregory Daniel Roach, Charli Sargent, Michele Lastella, and Tanita Cronje. 2020. How to manage travel fatigue and jet lag in athletes? A systematic review of interventions. *British Journal of Sports Medicine* 54, 16 (Aug. 2020), 960–968. https://doi.org/10.1136/bjsports-2019-101635

[21] Jisu Jung, Lyndal Wellard-Cole, Colin Cai, Irena Koprinska, Kalina Yacef, Margaret Allman-Farinelli, and Judy Kay. 2020. Foundations for Systematic Evaluation and Benchmarking of a Mobile Food Logger in a Large-scale Nutrition Study. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 4, 2 (June 2020), 1–25. https://doi.org/10.1145/3397327

[22] Taewan Kim, Haesoo Kim, Ha Yeon Lee, Hwarang Goh, Shakhboz Abdigapporov, Mingon Jeong, Hyunsung Cho, Kyungsik Han, Youngtae Noh, Sung-Ju Lee, and Hwajung Hong. 2022. Prediction for Retrospection: Integrating Algorithmic Stress Prediction into Personal Informatics Systems for College Students' Mental Health. In *CHI Conference on Human Factors in Computing Systems*. ACM, New Orleans LA USA, 1–20. https://doi.org/10.1145/3491102.3517701

[23] Urho M Kujala. 2021. Fitter, healthier and stronger? Many factors influence elite athletes' long-term health. *British Journal of Sports Medicine* 55, 2 (Jan. 2021), 77–78. https://doi.org/10.1136/bjsports-2020-102239

[24] Amanda Lazar, Christian Koehler, Theresa Jean Tanenbaum, and David H. Nguyen. 2015. Why we use and abandon smart devices. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, Osaka Japan, 635–646. https://doi.org/10.1145/2750858.2804288

[25] Ian Li, Anind Dey, and Jodi Forlizzi. 2010. A stage-based model of personal informatics systems. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, Atlanta Georgia USA, 557–566. https://doi.org/10.1145/1753326.1753409

[26] Louise Martin, Anneliese Lambeth, and Dawn Scott. 2006. NUTRITIONAL PRACTICES OF NATIONAL FEMALE SOCCER PLAYERS: ANALYSIS AND RECOMMENDATIONS. *Journal of Sports Science and Medicine* 5 (2006), 130–137.

[27] Felix Mata, Miguel Torres-Ruiz, Roberto Zagal, Giovanni Guzman, Marco Moreno-Ibarra, and Rolando Quintero. 2018. A cross-domain framework for designing healthcare mobile applications mining social networks to generate recommendations of training and nutrition planning. *Telematics and Informatics* 35, 4 (July 2018), 837–853. https://doi.org/10.1016/j.tele.2017.04.005

[28] Hannah McGuigan, Peter Hassmén, Nedeljka Rosic, and Christopher J Stevens. 2020. Training monitoring methods used in the field by coaches and practitioners: A systematic review. *International Journal of Sports Science & Coaching* 15, 3 (June 2020), 439–451. https://doi.org/10.1177/1747954120913172

[29] Francisco Monteiro-Guerra, Octavio Rivera-Romero, Luis Fernandez-Luque, and Brian Caulfield. 2020. Personalization in Real-Time Physical Activity Coaching Using Mobile Applications: A Scoping Review. *IEEE Journal of Biomedical and Health Informatics* 24, 6 (June 2020), 1738–1751. https://doi.org/10.1109/JBHI.2019.2947243

[30] Iñigo Mujika, Shona Halson, Louise M. Burke, Gloria Balagué, and Damian Farrow. 2018. An Integrated, Multifactorial Approach to Periodization for Optimal Performance in Individual and Team Sports. *International Journal of Sports Physiology and Performance* 13, 5 (May 2018), 538–561. https://doi.org/10.1123/ijspp.2018-0093

[31] Elizabeth L. Murnane, Tara G. Walker, Beck Tench, Stephen Voida, and Jaime Snyder. 2018. Personal Informatics in Interpersonal Contexts: Towards the Design of Technology that Supports the Social Ecologies of Long-Term Mental Health Management. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (Nov. 2018), 1–27. https://doi.org/10.1145/3274396

[32] Emma Neupert, Luke Gupta, Tim Holder, and Simon A Jobson. 2022. Athlete monitoring practices in elite sport in the United Kingdom. *Journal of Sports Sciences* 40, 13 (July 2022), 1450–1457. https://doi.org/10.1080/02640414.2022.2085435

[33] Kwok Ng and Tatiana Ryba. 2018. The Quantified Athlete: Associations of Wearables for High School Athletes. *Advances in Human-Computer Interaction* 2018 (Oct. 2018), 1–8. https://doi.org/10.1155/2018/6317524

[34] Australian Institute of Sport. 2024. Athlete Management System. https://www.ais.gov.au/ams

[35] Harm Op Den Akker, Valerie M. Jones, and Hermie J. Hermens. 2014. Tailoring real-time physical activity coaching systems: a literature survey and model. *User Modeling and User-Adapted Interaction* 24, 5 (Dec. 2014), 351–392. https://doi.org/10.1007/s11257-014-9146-y

[36] Maulishree Pandey, Michael Nebeling, Sun Young Park, and Steve Oney. 2019. Exploring Tracking Needs and Practices of Recreational Athletes. In *Proceedings of the 13th EAI International Conference on Pervasive Computing Technologies for Healthcare - Demos and Posters*. EAI, Trento, Italy. https://doi.org/10.4108/eai.20-

5-2019.2283726

[37] Ashwin A. Phatak, Franz-Georg Wieland, Kartik Vempala, Frederik Volkmar, and Daniel Memmert. 2021. Artificial Intelligence Based Body Sensor Network Framework—Narrative Review: Proposing an End-to-End Framework using Wearable Sensors, Real-Time Location Systems and Artificial Intelligence/Machine Learning Algorithms for Data Collection, Data Mining and Knowledge Discovery in Sports and Healthcare. *Sports Medicine - Open* 7, 1 (Dec. 2021), 79. https://doi.org/10.1186/s40798-021-00372-0

[38] Amon Rapp and Lia Tirabeni. 2018. Personal Informatics for Sport: Meaning, Body, and Social Relations in Amateur and Elite Athletes. *ACM Transactions on Computer-Human Interaction* 25, 3 (June 2018), 1–30. https://doi.org/10.1145/3196829

[39] Amon Rapp and Lia Tirabeni. 2020. Self-tracking while doing sport: Comfort, motivation, attention and lifestyle of athletes using personal informatics tools. *International Journal of Human-Computer Studies* 140 (Aug. 2020), 102434. https://doi.org/10.1016/j.ijhcs.2020.102434

[40] Samuel Robertson, Jonathan D. Bartlett, and Paul B. Gastin. 2017. Red, Amber, or Green? Athlete Monitoring in Team Sport: The Need for Decision-Support Systems. *International Journal of Sports Physiology and Performance* 12, s2 (April 2017), S2–73–S2–79. https://doi.org/10.1123/ijspp.2016-0541

[41] Dhruv R. Seshadri, Ryan T. Li, James E. Voos, James R. Rowbottom, Celeste M. Alfes, Christian A. Zorman, and Colin K. Drummond. 2019. Wearable sensors for monitoring the internal and external workload of the athlete. *npj Digital Medicine* 2, 1 (July 2019), 71. https://doi.org/10.1038/s41746-019-0149-2

[42] Barry Smyth, Aonghus Lawlor, Jakim Berndsen, and Ciara Feely. 2022. Recommendations for marathon runners: on the application of recommender systems and machine learning to support recreational marathon runners. *User Modeling and User-Adapted Interaction* 32, 5 (Nov. 2022), 787–838. https://doi.org/10.1007/s11257-021-09299-3

[43] Lindsay T. Starling and Michael I. Lambert. 2018. Monitoring Rugby Players for Fitness and Fatigue: What Do Coaches Want? *International Journal of Sports Physiology and Performance* 13, 6 (July 2018), 777–782. https://doi.org/10.1123/ijspp.2017-0416

[44] Christian Swann, Aidan Moran, and David Piggott. 2015. Defining elite athletes: Issues in the study of expert performance in sport psychology. *Psychology of Sport and Exercise* 16 (Jan. 2015), 3–14. https://doi.org/10.1016/j.psychsport.2014.07.004

[45] Emer Van Ryswyk, Richard Weeks, Laura Bandick, Michaela O'Keefe, Andrew Vakulin, Peter Catcheside, Laura Barger, Andrew Potter, Nick Poulos, Jarryd Wallace, and Nick A. Antic. 2017. A novel sleep optimisation programme to improve athletes' well-being and performance. *European Journal of Sport Science* 17, 2 (March 2017), 144–151. https://doi.org/10.1080/17461391.2016.1221470

[46] Michalis Vrigkas, Christophoros Nikou, and Ioannis A. Kakadiaris. 2015. A Review of Human Activity Recognition Methods. *Frontiers in Robotics and AI* 2 (Nov. 2015). https://doi.org/10.3389/frobt.2015.00028

[47] S. Wilson-Barnes, L. P. Gymnopoulos, K. Dimitropoulos, V. Solachidis, K. Rouskas, D. Russell, Y. Oikonomidis, S. Hadjidimitriou, J. María Botana, B. Brkic, E. Mantovani, S. Gravina, G. Telo, E. Lalama, R. Buys, M. Hassapidou, S. Balula Dias, A. Batista, L. Perone, S. Bryant, S. Maas, S. Cobello, P. Bacelar, S. A. Lanham-New, and K. Hart. 2021. PeRsOnalised nutriTion for hEalthy livINg: The PROTEIN project. *Nutrition Bulletin* 46, 1 (March 2021), 77–87. https://doi.org/10.1111/nbu.12482

[48] Santosh Kumar Yadav, Kamlesh Tiwari, Hari Mohan Pandey, and Shaik Ali Akbar. 2021. A review of multimodal human activity recognition with special emphasis on classification, applications, challenges and future directions. *Knowledge-Based Systems* 223 (July 2021), 106970. https://doi.org/10.1016/j.knosys.2021.106970

[49] Luyao Yang, Osama Amin, and Basem Shihada. 2024. Intelligent Wearable Systems: Opportunities and Challenges in Health and Sports. *Comput. Surveys* 56, 7 (July 2024), 1–42. https://doi.org/10.1145/3648469