Understanding the Person-specific Predictors of Athlete Performance

Ubicomp/ISWC 2024 Doctoral Colloquium

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CCS CONCEPTS

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

KEYWORDS

wearables, athletes, personal informatics, tracking, user needs, sportsHCI

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1 PROBLEM STATEMENT

Physical health, mental health, nutrition, and sleep are four important pillars that affect athlete performance. Within these pillars, there are over twenty variables that affect an athlete's development and performance [5, 7, 8, 10, 15, 45, 52, 73], however, to our knowledge, there is no analytical tool for individual athletes to understand how these interrelated variables quantitatively affect their performance. Little is understood about the challenges of making use of rich collections of diverse tracking data and current athlete management and recommender systems fall short of providing personalised feedback about the athlete's short- and long-term goals.

Analytical methods appropriate for highly heterogeneous and multivariate data need to be used to personalise feedback to athletes, such as within-subject classification methods. Current research and industry methods lack the translation of both linear and non-linear intra- and inter-individual variations of relationships onto an interactive network visualisation for athletes. This research aims to enable athletes to make decisions that optimise their performance by harnessing their own personal data. Athletes should be able to easily understand and explore their rich, quantified, multivariate self.

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2 RELATED WORK

This section will discuss relevant literature in relation to what variables athletes want to collect data on, what tools are currently available to athletes to collect and understand their data, and the challenges of collecting and analysing long-term personal data.

2.1 What do athletes want to know?

The increasing availability of sensor technologies and easy-to-use journal tools make it feasible for athletes to collect diverse forms of personal data that may be valuable for understanding their performance. Sport science research has placed greater weight on coaches' opinions–what variables coaches want to track and how systems can best benefit coaches. Athletes are often not included in the process of recording and analysing performance movements [10], but when given the opportunity, athletes fail to adhere to training-monitoring systems because of the lack of feedback they receive on their monitoring data [55, 56]. Most studies within sports science focus on improving training-monitoring systems based on coach needs (see [52, 74, 77]). Studies that tend to focus on athlete users often come within the HCI discipline. For example, Rapp and Tirabeni [66, 67] aimed to understand what athletes want to track, how they track, and how they use their personal informatics tools. Op Den Akker et al. [60] investigated how real-time physical activity coaching systems could be tailored better to the user. Smyth et al. [73] and Donciu et al. [23] use case studies and usability studies with end-users to develop recommender systems for runners. Although there has been investigation into making athlete management and recommender systems better, athletes need to be involved within the design and evaluation process to a greater extent. Grand challenges within SportsHCI include the lack of knowledge of how to model the multifaceted athlete in interactive technologies and how to design systems to athlete's feedback and sense-making [25]. Systems need to consider both bodily and contextual performance markers when analysing athletes for performance optimisation. Systems also need to consider how to optimise the athletes' decision making capabilities when using sport recommender systems.

Based on Epstein et al. [29] Personal Informatics model, there are three major stages of personal informatics systems: configuration, data capture, and feedback. There is a lack of knowledge of athlete perspectives for each of these stages. SportsHCI needs to investigate athletes' motivations and goals behind deciding to track, athletes' motivations behind selecting personal data tracking tools and variables, and how athletes reflect and make decisions based on their personal data, and why athletes continue or stop tracking. This PhD research project aims to contribute towards building knowledge on these athlete perspectives.

2.2 Current tools and systems

The increasing availability of sensor technologies and easy-to-use journal tools make it feasible for athletes to collect diverse forms of personal data that may be valuable for understanding their performance. Analysing multiple factors together can provide a data-driven holistic understanding of an individual's talent development and sporting performance [32, 54, 73]. But to gather personalised insights of multiple pillars on an individual athlete, time series data is needed (N-of-1 data), which calls for long-term multi-variate tracking [28].

The use of rich collections of diverse tracking data for individuals and groups has been explored in multiple disciplines, including sport science, health science, and personal informatics. Studies that investigated the relationship between physical health markers and nutrition in relation to athlete training and performance include Mata et al. [50], Donciu et al. [23], Hakkila et al. [36], Heather et al. [39], and Martin et al. [49]. Other studies focused on the relationship between physical health and psychological markers in relation to athlete identity and performance such as Ng and Ryba [57], Rapp and Tirabeni [67], Abdullah et al. [2], Heather et al. [39], and Van Ryswyk et al. [78]. Generally, previous work has explored ways to enable coaches and athletes to reflect on one or two of the four pillars, typically over a short term. Despite the general consensus in the literature that multiple factors and processes can affect an individual's health and performance, there have been limited quantitative explorations of all four factors together–studies generally analyse one or pairs of the four factors in relation to athlete performance. There seems to be a gap between the promised combined use of multiple data streams and practice. The design of interactive systems that can support the performance optimisation of an athlete, who is treated as a multifaceted individual, is a key challenge in SportsHCI [25]. Integration of plentiful wearables, easy-to-use self-reported journals, and interactive systems have not been realised for the four pillars.

Although Smyth et al. [73] mentions how all four pillars and environmental context can affect a recreational runner's performance, only physical activity from Strava was measured and served as input to the machine learning algorithms that produce recommendations. Similarly, Donciu et al. [23] also produced a recommender system for runners, supplementing physical activity data with nutrition data to personalise recommendations for pre- and post-running nutrition. However, neither recommender systems collected data on recovery measures, such as sleep or mental state, to personalise workout and nutrition recommendations. Sports recommender systems that do analyse at least two of the four pillars often do not support bundled recommendations [33]. For example, current sports recommender systems do not provide food recommendations with recommendations for training sessions and sleep requirements.

In the industry, there are multivariate tracking tools and data management systems for athletes, such as Whoop and the AMS. Whoop, founded in 2012 with over 25K users, is one of the earliest wearables to include sleep and recovery tracking and it aims to deliver value for professional athletes using an associated mobile application [83]. Whoop aims to personalise tracking of workout and recovery measures both short and long term. Similarly, the AMS, an Australian athlete management system created by the Australian Institute of Sport in partnership with Smartbase, also aims to track physical load and recovery on professional athletes. The AMS was created in 2013, is used by 45 different Australian organisations, 12K athletes, and 5K staff members, and has over 3 billion records of data [58]. Both systems can collect data from all four pillars (i.e., physical health, mental health, sleep, and nutrition), however both systems lack personalisation of feedback in relation to short- and long-term individual goals. Neither system allows users to input sport-specific goals for each workout session or long-term performance goals. As a result, feedback is limited to simple correlations between two variables of interest or require third parties, such as sport scientists or data analysts, to interpret and contextualise the data for decision making purposes. Both systems are unable to provide personalised recommendations that take into consideration all four pillars and goals. Athletes and coaches alike are unsatisfied with current sport systems and feel the feedback processes are ineffective [33, 55].

Considering the learnings from sports science and personal informatics literature [33, 61, 74], an ideal athlete management system would have the following: integrates multiple wearable data sources automatically, integrates easy to use self-report journals, feedback would be easy to understand and easily used towards improving on goals. This PhD project aims to contribute towards building a useful athlete management system that can integrate individual goals and provide effective personalised feedback and recommendations.

2.3 Long-term diverse data collection and analysis

Collecting and analysing multivariate N-of-1 health data is a data mining challenge that some scholars have begun to unpack (see [12, 21, 41, 70, 80]). One of the main challenges in long-term data collection are the gaps in the data at both micro and macro level [29]. An athlete might decide to temporarily stop using their tracking device or filling out their journal. Why these gaps occur depend on the individual's context, but the literature has identified that if automation of data collection is limited, cost of tracking effort increases, and quality of long-term data can be compromised [16, 29, 46]. Currently, most non-athletic performance facets are measured using self-reported measures which have manual or semi-automatic types of data collection. This makes long-term data on mental health and nutrition especially difficult to collect and analyse. Since athletes and coaches alike want to see their long-term data in relation to sport-specific goals [61, 74], key challenges with long-term tracking of personal information are not only balancing the effort of tracking with the quality of data, but also interpreting the data with contextual information.

Analysing N-of-1 multi-variate data poses a whole new set of challenges. There are many different types of analytical methods that have been used from simple descriptive analyses and correlations to complex machine learning algorithms and network models. There are two main challenges of analysing long-term N-of-1 multivariate data: bridging nomothetic and idiographic methods of analysis, and exploring both linear and non-linear multivariate relationships.

Athletes are (meaningful) outliers from the general population. They participate in physically and psychologically taxing activities for long periods of time, are extremely disciplined with their nutrition and recovery, and the makeup of their body and mind changes over the course of their talent development journey. These behavioural changes can be intentional and unintentional; the processes athletes experience are not ergodic. Normative biostatistical methods, commonly used to analyse health data of individuals, assumes the homogeneity of effects across people and time and assumes ergodicity–that processes are stationary and the same model can be applied to all processes [11, 38, 69]. If a phenomenon is not ergodic (i.e., an individual athlete's response to a training style over time is not representative of a group/population of athletes), nomothetic findings that are developed and measured from the collective cannot be applied to the individual [38].

Sport science aims to build knowledge around maximising the intentionality of athlete performance changes. At the elite level, training is greatly personalised, but sport science is heavily reliant on nomothetic methods (methods that uncover a generalised prediction that is true in the aggregate examine interindividual variation in the data–variation between or across people). There is great heterogeneity across athletes and time in sport science studies, and nomothetic approaches may not always be appropriate. While idiographic measures (methods that aim to assert specific observation and predictions about individuals by examining inter-individual variation–variation within a person over time) are currently used to identify problems [30, 59, 81], using nomothetic research or heuristic intuition to drive interventions will not always be optimal for all athletes. "Idionomic" models, a term coined by [37], combines the insights from idiographic and nomothetic approaches. Idionomic models begin with idiographic models and build up to nomothetic models if and only if it improves the idiographic fit. That way, group-level insights are produced without losing individual-level information. Therefore, idionomic models can offer a data-driven approach to improve the effectiveness of personalised interventions for athletes.

Current methods that aim to reconcile nomothetic and idiographic approaches include person-specific models derived from within-subject classification methods (see [1, 22, 26, 27, 34, 35, 42, 62, 64, 65, 71, 75, 82]). These methods often use algorithms such as Linear Discriminant Analysis (LDA), Shape Classification Networks (SCN), Graphical Gaussian Models (GGM), and autoregressive models (e.g., Vector Autoregression (VAR) and Individual Autoregressive Integrated Moving Average with Explanatory Variable (i-ARIMAX)), which are often bound by underlying linear assumptions. Some scholars have attempted to overcome linearity constraints of the above mentioned statistical methods by using machine learning or non-linear correlation analyses (see [3, 14, 19, 32, 40, 41, 53, 75]). Non-linear and multi-model (ensemble models) methods used by researchers include self-organising maps, clustering, random forests, nonlinear autoregressive models, and deep learning methods. These are not always successful in overcoming linearity assumptions, as many machine learning methods have black box algorithms that might still be applying linear correlations under the hood. Furthermore, applying these non-linear methods on heterogeneous data still violates the ergodicity assumption.

Mixture modelling is a statistical technique that can be used on heterogenous data, such as Latent Classification Differential Model (LCDM) and Deep Guassian Mixture Modelling (DGMM) [44, 71, 79]. Although these unsupervised machine learning methods in combination with prior knowledge can help identify subgroups of individuals who substantially deviate from the overall normative effect (e.g, identifying long versus short distance running athletes), these methods are prone to overfitting and often require cross-validation to confirm their results. Literature that specifically analyses athlete data (see [2, 4, 6, 17, 23, 32, 36, 39, 40, 47, 49–51, 57, 63, 67–69, 75, 78, 81]) have used quantitative analytical techniques, however have not attempted to apply non-nomothetic approaches such as mixture modelling.

Amateur and elite athlete studies have mainly been idiographic in nature and analysed qualitatively (see [5, 8–10, 13, 18, 30, 31, 59, 76]). While qualitative interviews of athletes and coaches can provide valuable insights into athlete performance and experience, combining nomothetic and idiographic techniques in sport science research could supercharge a comprehensive understanding of the factors that contribute to an athlete's success. Some sport psychologists and nutritionists have attempted to account for intra-individual differences, however lack statistical rigour. Although Drew [24] mentioned technologies that can aid in the process of addressing challenges of intra-individual variation in the context of nutrition, no concrete quantitative method was proposed. Similarly, Kaufman [43] presented a qualitative discussion of individual differences in elite performance studies rather than a quantitative approach. Bailey [7] proposes single-subject designs to capture individual-level data, however fails to demonstrate statistically how nomothetic and idiographic approaches can be bridged. Although Cheung et al. [20] explored both nomothetic and idiographic approaches, they treated the two methods as opposing and tested each separately when modelling daily exercise behaviours. Scholars have attempted to address nomothetic and idiographic approaches in sport science, but they have been unsuccessful in discussing or implementing an idionomic method. Other than the scholars cited in this paper, no other studies were found that explicitly addressed issues with or the complementary nature of nomothetic and idiographic statistical approaches in relation to athlete long-term data.

2.4 Research questions

Based on the literature review and the grand challenges SportsHCI faces [25], these are the research questions this PhD project aims to address:

RQ1 - What do athletes want to track and how? RQ1a - Which of the four pillars do athletes find value in and want to track in relation to their performance? RQ1b - What real-time feedback and post-real-time feedback do athletes want to have? RQ1c - What athlete-orientated challenges need to be addressed?

RQ2 - How to build an interactive system that treats an athlete like a multifaceted individual in the real sporting world?

RQ2a - How to design the technology for the longitudinal nature of athletic performance? RQ2b - How to support relationships between athletes and other stakeholders (coaches, sport scientists, practitioners)? RQ3c - How to support the athlete beyond bodily performance advice and non-athletic performance facets?

3 METHODOLOGY

3.1 Need Finding Study

To address RQ1, we conducted a need finding study[1] using a questionnaire. The study [72] was able to find which pillars athletes perceived as important for their performance, which pillars athletes actually monitor to improve their performance (RQ1a), and which pillars do athletes find useful to monitor using current athlete management platforms (RQ1c). Results are further discussed in the evaluation section below.

To understand in greater depth current challenges athletes face (RQ1c) and how athletes would like to receive real-time and post-real-time feedback (RQ1b), three focus groups will be conducted[2]. One focus group will be composed of only athletes, a second with only coaches, and a third with both athletes and coaches. These relationships between athletes and coaches will hopefully also shed light on how athlete-coach relationships can be supported in athlete monitoring systems (RQ2b).

3.2 Co-designing Athlete Monitoring System

To address RQ2, a co-design method to build an athlete monitoring system will be employed. This will involve a) building an idionomic ensemble model that analyses long-term athlete data, b) designing a system that integrates multiple wearable data sources automatically, c) integrates easy-to-use self-report journals, d) caters towards athlete-orientated goals, and e) provides feedback that is easy to understand and be used to improve on goals and performance. More on the evaluation steps of this stage of the PhD will be discussed in the Evaluation section below.

4 EVALUATION

4.1 Need Finding Study

Athletes who answered the questionnaire overwhelmingly supported the notion that all four pillars are important to track for their performance [72]. This finding aligns with the broader sports science literature (Baker 2020). However, results from the need finding study [72] showed a mismatch between perceived value versus actual tracking of nutrition, sleep, and mental health, but consistency on physical health. Respondents were also divided over the usefulness of a current athlete management system commonly used in Australia called the AMS [58]. Overall, it seems the greater reliance on self-reported measures, the less a pillar is tracked. This finding aligns with Personal Informatics and HCI literature–the cost of tracking effort increases with manual self-reported measures, and quality of long-term data can be compromised [16, 29, 46].

Despite alignment between perceived importance and actual tracking of physical health, a questionnaire respondent mentioned that they, "don't think there is a platform out there which monitors [physical health] well enough." This comment aligns with the fact that many current sports recommender systems lack integration of sport-specific goals and real-time feedback [25, 33, 48, 61]. Athletes and coaches alike seem to want systems that personalise insights in relation to not only short-term goals, but also long-term and sport-specific goals.

Overall, this need finding study was able to identify what athletes want to track and what challenges they currently face. Findings are similar to the gaps in the literature identified in the 'Related Work' section and this study demonstrates that there is a need to improve on the lack of knowledge about how to build an interactive system that treats an athlete like a multifaceted individual in the real sporting world.

4.2 Co-designing Athlete Monitoring System

To test and validate the idionomic ensemble model that analyses long-term athlete data, a proof-of-concept study will be conducted. Two variables associated with each pillar will be collected from 20 athletes (ideally equally ratioed male and female athletes) over two months, with a minimum of 100 within-person data points. Data will be collected from a wearable, ideally Whoop, as it has the capabilities to collect data on all four pillars.

To test and validate whether the monitoring system effectively caters towards athlete-orientated goals and provides feedback that is easy to understand and can be used to improve athlete performance, iterative usability studies will be conducted throughout the design phase. This will ensure that user needs (i.e., athlete needs) are met and the challenges they face with current athlete management systems are addressed in the proposed athlete monitoring system.

5 CONTRIBUTION

This PhD project aims to advance the field of personalised sport analytics. Elvitigala et al. [25] identified the "grand challenges" within SportsHCI and this paper directly contributes to the following gaps in research and industry:

(1) Contibuting to the lack of knowledge of how interactive technologies can support **performance optimisation**, including how to design real-time systems that consider coach and athlete **feedback** and sense-making, and how to design interactive technologies for the **longitudinal nature** of athlete performance.

(2) Contributing to the lack of knowledge of how to design interactive technologies that support coach-athlete relationships and **athlete-orientated** challenges.

(3) Contributing to the lack of knowledge of how to design interactive technologies for the athlete being a multifaceted individual, in particular designing technologies that support athletes across the **four pillars**. This includes exploring idionomic techniques of **analysing multivariate individual long-term data**.

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