Think
Biosolution

# Technology Review: The Impact of Personalized Coaching Using Wearables, Compared to Training with a Coach

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# 1. Introduction

Improvements in technology continue to raise the tracking efficiency and accuracy of wearable devices (Camomilla et al., 2018).[1] In addition to motion sensors[2] that track physical activity metrics such as distance and acceleration, newer models of wearable devices are equipped with physiological sensors[3] that track biomarkers such as impact force and stress; and bio-vitals such as heart rate and body temperature (Seshadri et al., 2017).[4]

Innovative software applications use machine learning algorithms to interpret data tracked by wearable devices (Lazarevich, 2019).[5][6] This combination of sensors and software makes up multimodal digital coaching platforms that generate actionable insights on the physical and mental health of users (Seshadri et al., 2017).

In comparison to alternative laboratory based systems, wearable devices are considered to be practical and versatile (Ermes et al., 2008).[7] As a result, interest in digital coaching platforms has increased over the last decade (Camomilla et al., 2018). This paper considers the impact of personalised coaching using wearables by exploring benefits, limitations and use cases.

# 2. Personalized Digital Coaching Platform

Digital coaching platforms receive data from a wide range of wearable devices including headbands, headphones, harnesses, glasses, wristbands, watches, rings, belts, running shoes and others (Rodrigues et al., 2018).[8] In practice, some wearable devices are more suitable for tracking specific activities than others. For example, *Push* discarded a conventional smartwatch form factor while developing a wearable device for CrossFit athletes. Instead, the company settled on a compression sleeve considered to be unobtrusive during CrossFit activity.[9][10]

Digital coaching platforms identify, track and analyze a wide range of activities involving athletes, medical patients, physical workers and other personal users. To accomplish this, custom machine learning algorithms develop domain specific expertise by referring to training data with recognizable patterns from similar

[1] https://www.mdpi.com/1424-8220/18/3/873/pdf

[2] Location sensors (i.e., GPS) and sensors (i.e., accelerometers, magnetometers, gyroscopes)

[3] Heart rate monitor, temperature monitor, glucometer, SPO2 etc

[4] https://ieeexplore.ieee.org/abstract/document/7831543

[5] https://www.iotforall.com/benefits-ai-in-wearables/

[6] https://www.wareable.com/wearable-tech/ai-smart-wearables-present-future-795

[7] https://ieeexplore.ieee.org/document/4358887

[8] https://www.researchgate.net/publication/322261039_Enabling_Technologies_for_the_Internet_of_Health_Things

[9] https://www.wareable.com/sport/the-best-gym-fitness-tracker-band-weights-wearables

[10] https://www.wareable.com/wearable-tech/nexus-crossfit-wearable-push-kickstarter-6346

scenarios.[11] Moreover, digital coaches monitor contextual data to incorporate the impact of external factors. For example, *Game Your Game* equips its wearable devices with a custom virtual assistant that provides golfers with actionable insights after analyzing past shots, identifying unique tendencies and considering external factors such as weather and golf course elevation (Lazarevich, 2019).[12]

Digital coaching platforms provide users with audio or visual feedback after interpreting data. This feedback generally consists of actionable insights and personalized recommendations. Wearable devices with output functions such as smartwatches or headphones provide feedback directly. Other non-interactive wearable devices such as running shoes provide feedback through smartphones and other third-party devices. Alternatively, wearable devices provide direct haptic feedback with a unique advantage: users do not have to break concentration during activity and vibration patterns can subtly coach improvements in sensitive scenarios such as surgery (Culbertson, Schorr and Okamura, 2018).[13][14]

# 3. Benefits

## *3.1. Bio-data*

Digital coaching platforms track and interpret large amounts of user data. Most importantly, this includes biometric and biovital data that traditional coaches are unable to observe or quantify. This access to data allows digital coaching platforms to empirically consider a wider range of physical and physiological factors. For example, *NoMo Diagnostics* identifies concussions that occur with no signs of external trauma by monitoring biometric and biovital data. This reduces the risk of long-term neurological damage by eliminating "fairly subjective judgments about who should be removed from a game to receive a full neurological evaluation" (Age of Robots, 2019).[15]

## *3.2. Precision*

Digital coaches can quantify user activity in a consistent and reliable manner. As well as quantitative feedback (e.g. how far or fast a user runs), qualitative feedback (e.g., how *well* a user runs) can be summarized by a specific value. This allows digital coaching platforms to evaluate training outcomes more precisely than traditional coaches. For example, instead of practicing with imperfect form for an arbitrary period of time, *Pivot* encourages

[11] https://pdfs.semanticscholar.org/153b/1ac383848b7d672966c0d44c4f950e762456.pdf

[12] https://www.iotforall.com/benefits-ai-in-wearables/

[13] https://www.annualreviews.org/doi/full/10.1146/annurev-control-060117-105043

[14] https://ieeexplore.ieee.org/document/5626270

[15] https://ageofrobots.net/new-smart-helmet-could-spot-concussions-in-real-time/

users to hit a number of perfect swings based on training data from tennis experts (CGTN America, 2016).[16] Over time, more precise training can provide a significant edge in sports where small margins make all the difference.

### 3.3. Prediction is better

Digital coaching platforms use machine learning to make predictions based on the real time analysis of user data. For example, digital coaching platforms can predict the likelihood that users will meet their performance goals and adjust personalized recommendations to ensure that targets are met (Dijkhuis et al., 2018).[17] Digital coaching platforms also predict future health events such as injuries from training with poor form or excessive effort. In the long run, collecting user data contributes towards the development of machine learning algorithms for “automated health event prediction, prevention and intervention” (Dunn, Runge and Snyder, 2018).[18]

### 3.4. 24/7 coaching

Digital coaching platforms continuously track and analyze user data. This creates an opportunity to monitor the impact of behavioral characteristics outside training sessions or clinical settings. As a result, digital coaching platforms develop a holistic understanding of users and can make recommendations aimed at discouraging sedentary behavior (Wilde et al., 2018).[19] In comparison, recommendations from traditional coaches are limited to periods of observed activity.

## 4. Unique use cases

Alongside the complimentary benefits in existing coaching scenarios, digital coaching platforms open up possibilities in scenarios where traditional coaching is less practical. For example, digital coaching platforms provide on the job training and safety monitoring for construction workers (Awolusi et al., 2018). This provides an opportunity for companies to improve efficiency and control costs by smoothing transitions between workers and reducing time spent on individual trainings.

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[16] https://www.youtube.com/watch?v=pKVkpjtlNBk

[17] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5856112/

[18] https://www.futuremedicine.com/doi/full/10.2217/pme-2018-0044

[19] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6016566/

In similar context, digital coaching platforms allow insurance companies to predict health risks and dynamically price premiums for individual members. To accomplish this, *Boundlss* provides a platform for members to share their biometric and behavioral data for insurers to monitor. Insurers also use this platform to provide members with engaging health, wellbeing and disease prevention programs.[20] In line with its core vision to "shift the focus from treating the disease to preventing the disease, which is in the interest of the insurer", *Boundlss* aims to "accelerate insurance company transformation to long term preventative health partners".[21][22][23]

# 5. Limitations

Digital coaching platforms lack the physical and motivational characteristics of traditional coaches. This makes it difficult to ensure that recommendations are successfully implemented by users. It is possible to improve the experience by modeling digital coaching platforms to handle the potentially conflicting goals and motivations of their users (Lindgren et al., 2017). However, as studies show that "motivation is a dynamic and contextually driven phenomenon", machine learning algorithms will require large amounts of data to consistently motivate users (Asimakopoulos, Asimakopoulos and Spillers, 2017).[24]

Digital coaching platforms typically receive limited amounts of data from a single wearable device. To personalize recommendations even further, it is necessary to incorporate a wider range of relevant data. For example, access to other relevant data such as user medical records may improve the quality of personalized recommendations (Rodrigues et al., 2018). However, while increased access to data generally improves machine learning algorithms, continuous tracking and analysis of user data may not always generate better insights on physical or mental health. In practice, wearable devices may observe negative health indicators that are unlikely to re-appear and wrong interpretations of such irregular data may lead to overtreatment (Kuchler, 2019).

[20] http://www.boundlss.com/health-programs

[21] https://www.insurancejournal.com/news/national/2018/04/23/486869.htm

[22] https://www.startupbootcamp.org/blog/2018/02/how-digitizing-healthcare-could-revolutionize-insurance/

[23] http://www.boundlss.com/data-analytics

[24] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6016566/

## 6. Summary

Wearable devices track large amounts of user data (i.e. movement data, biometric data, and biovital data) using various combinations of motion and physiological sensors. Machine learning algorithms analyze user data and generate actionable insights by referring to training data with recognizable patterns from similar scenarios. Additional tracking and analysis of contextual data allows digital coaching platforms to consider the impact of external factors and adjust personalized recommendations to suit specific scenarios.

Digital coaching platforms can track mobility, assess physical demands, classify activities and analyze technique (Camomilla et al., 2018).[25] Key factors that influence the quality of personalized coaching recommendations are influenced by the accuracy of sensors; the relevance of training data; the quality of machine learning algorithms; and the effectiveness of feedback mechanisms.

Motivating users to act on recommendations is a key challenge for digital coaching platforms. In order to overcome this, it is important to develop systems that have strategies to handle conflicting user motives and preferences (Lindgren et al., 2017).[26] It is also important to acknowledge that the necessary deep analysis of data required to achieve this will require collaboration. Thus, efforts to share and combine multiple sources of data will reduce the effects of device specific limitations and provide more holistic recommendations.[27][28]

Technological improvements are likely to shift the long-term scope of traditional coaching. In the meantime, recent developments are attracting the attention of regulators in the healthcare industry. For example, *Apple* received US Food & Drug Administration clearance for the heart monitoring features on its wearable watch device (Sawh, 2019). This sets the pace for further progress in the intersection between wearables and healthcare.

[25] https://www.mdpi.com/1424-8220/18/3/873/pdf

[26] https://pdfs.semanticscholar.org/ffe5/34f1e6d492623954be9b7a00df0ef825608e.pdf

[27] https://hartfordinsurtechhub.com/industry-spotlight-wearables-health-can-combine-dominate-technology-industry/

[28] https://www.theguardian.com/technology/2015/jan/06/future-wearable-technology-analysing-data

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