Monitoring von Belastungs- und Beanspruchungsmarkern zur individualisierten Steuerung von Trainingsprozessen mithilfe tragbarer Sensorik (Wearable Technology)

Inaugural-Dissertation

zur Erlangung der Doktorwürde der

Fakultät für Humanwissenschaften

der

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2020

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Tag des Kolloquiums: 02.03.2021

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Abkürzungsverzeichnis

Abkürzung	Erklärung
ANS	Autonomes Nervensystem
App	Smartphone Anwendung (Application)
bpm	Herzschläge pro Minute
FDA	Food and Drug Administration
FIFA	Fédération Internationale de Football Association
HRR	Herzfrequenzabfall
HRV	Herzfrequenzvariabilität
IAAF	International Association of Athletics Federations
ICC	Intraklassenkorrelationskoeffizient
p	Statistisches Signifikanzniveau
POCT	Point-of-Care-Testing
r	Korrelationskoeffizient
UV	Ultraviolett
$\dot{V}O_{2peak}$ ($ml*kg^{-1}*min*^{-1}$)	Maximale Sauerstoffaufnahme ermittelt während einer Leistungsdiagnostik
Wearables	Tragbare Sensortechnologie
CV%	Variationskoeffizient (in Prozent)

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Studienverzeichnis

1. Studie 1: Düking P, Hotho, A, Holmberg HC, Fuss FK, Sperlich B. (2016). Comparison of Non-Invasive Individual Monitoring of the Training and Health for Athletes with commercially available Wearable Technologies. Front Physiol. 7:71
2. Studie 2: Düking P, Fuss FK, Holmberg HC, Sperlich B. (2018). Recommendations for assessment of the reliability, sensitivity and validity of data provided by wearables sensors designed for monitoring physical activity. JMIR Mhealth Uhealth;6(4):e102
3. Studie 3: Düking P, Holmberg HC, Frenkel MO, Giessing L, Köhler K, Sperlich B. (2020). Assessment of the validity of four commercially available wrist-worn wearables for monitoring heart rate and energy expenditure while sitting or performing light to vigorous physical activity. JMIR mHealth and uHealth. preprint
4. Studie 4: Düking P, Zinner C, Reed JL, Holmberg HC, Sperlich B. (2020). Predefined vs. data guided training prescription based on autonomic nervous system variation: A systematic review. Scand J Med Sci Sports (submitted, 26.02.2020)
5. Studie 5: Düking P, Achtzehn S, Holmberg HC, Sperlich B (2018). Integrated Framework of Load Monitoring by a Combination of Smartphone Applications, Wearables and Point-of-Care Testing Provides Feedback that Allows Individual Responsive Adjustments to Activities of Daily Living. Sensors (Basel). 19;18(5)
6. Studie 6: Düking, P, Stammel C, Sperlich B, Sutehall S, Muniz-Pardos B, Lima G, Kilduff L, Keramitsoglou I, Li G, Pigozzi F, Pitsiladis YP. (2018). Necessary Steps to Accelerate the Integration of Wearable Sensors Into Recreation and Competitive Sports. Curr Sports Med Rep. (6):178-82.

I. Kurzzusammenfassung

Trainingsprozesse sollten individualisiert und situativ an das Verhältnis zwischen Belastung bzw. Beanspruchung und Erholung angepasst werden, um optimale physiologische Adaptionen und Leistungsverbesserungen zu erzielen. Dazu müssen verschiedene Belastungs- und Beanspruchungsmarker erfasst, analysiert und interpretiert werden. Durch technologische Entwicklungen im Bereich tragbarer Sensorik (Wearables) ist es inzwischen möglich, eine Vielzahl an relevanten Belastungs- und/oder Beanspruchungsmarkern in der Praxis zu erheben. Übergeordnetes Ziel der Dissertation war, den Einsatz von Wearables zum Monitoring von Belastungs- und/oder Beanspruchungsmarkern zur individualisierten und situativ angepassten Steuerung von Trainingsprozessen aus trainingswissenschaftlicher Perspektive zu untersuchen.

Es wurden sechs Studien durchgeführt. Es konnte gezeigt werden,

1. dass einige, aber nicht alle relevanten Belastungs- und Beanspruchungsmarker mit derzeit kommerziell erhältlichen Wearables erfasst werden können (*Studie 1*),
2. dass viele Marker welche von Wearables erhoben werden nicht auf Reliabilität und/oder Validität hin untersucht worden sind und/oder dass sich die Reliabilität und/oder Validität zwischen Wearables und verschiedenen sportlichen Aktivitäten unterscheidet und deren Anwendung daher limitiert ist (*Studie 1,2,3*),
3. dass die Apple Watch Series 4, gefolgt von der Polar Vantage V, die derzeit beste Validität zur Erfassung der Herzfrequenz bei Athleten während verschiedenen Laufintensitäten aufweist (*Studie 3*).
4. dass bei Läufern ein individualisiert gesteuerter Trainingsprozess (basierend auf Daten des autonomen Nervensystems erfasst durch Wearables) zu größeren Leistungsverbesserungen

und ausgewählten submaximalen physiologischen Adaptionen führt, als ein nicht individualisiert gesteuerter Trainingsprozess (*Studie 4*),

5. dass ein System benötigt wird, welches verschiedene Technologien zur weiteren Ausdifferenzierung eines individualisiert gesteuerten Trainingsprozesses vereint (*Studie 5*).

Es bleiben weitere Fragen offen die Klärung bedürfen, wenn Wearables zum Monitoring von Belastungs- und/oder Beanspruchungsmarkern zur individualisierten Steuerung von Trainingsprozessen verwendet werden sollen. Zu diesen Fragen gehören unter anderem:

1. Welche Auswahl an Belastungs- und/oder Beanspruchungsmarkern sowie Wearables in Abhängigkeit der Sportart, der Athletenpopulation und der Trainingsphase optimal ist,
2. ob die Erfassung von großen Datenmengen sowie die Anwendung von Big Data Analysen einen Mehrwert bei der individuellen Steuerung von Trainingsprozessen liefern,
3. wie ein (Bio-)Feedback optimal gestaltet wird,
4. wie Trainer mit Wearables interagieren,
5. welche Abänderung des Trainingsprozesses in Abhängigkeit der jeweiligen Sportart und Athletenpopulation auf Basis welches Parameters optimal ist.

II. Abstract

Training prescription should be individualized and responsively adjusted to balance training load and recovery in order to promote optimal physiological adaptations and enhance performance. This procedure requires monitoring of external and internal load markers. Due to the technological developments in the field of wearable sensor technologies (wearables), a variety of markers can be monitored. The overall goal of this thesis was to investigate the use of wearables for monitoring external and internal load markers for the individualization and responsive adjustments of training processes from a training science perspective.

Six studies were conducted. The main findings are as follows:

1) some, but not all, external and internal load markers can be monitored with commercially available wearables (*study 1*),
2) many markers which are monitored by wearables have not been examined for reliability and/or validity and/or that the reliability and/or validity differs between wearables and between different sporting activities which limits their usefulness (*study 1, 2, 3*),
3) the Apple Watch Series 4, followed by the Polar Vantage V, revealed the highest validity to monitor heart rate of athletes during different running intensities (*study 3*),
4) in runners individualization and responsive adjustments of training processes (based on data from the autonomic nervous system monitored by wearables) leads to greater performance improvements and selected submaximal physiological adaptations than a predefined training prescription (*study 4*),
5) a system needs to be developed which combines different Wearables for further differentiation of an individualization and responsively training process (*study 5*).

There are questions that need clarification if Wearables shall be used to monitor external or internal load markers for the individualization and responsive adjustments of training processes. These questions include:

1) Which selection of external and internal load markers and wearables is optimal depending on the type of sport, the athlete population and the training phase?
2) Does the acquisition of large amounts of data and the application of big data analyses such as the artificial intelligence adds value in the individualization and responsive adjustments of training processes?
3) How is the (bio-)feedback optimally established?
4) How do coaches interact with data derived from wearables?
5) Which responsive adjustment of the training process is optimal, depending on the respective sport and athlete population?

1. Einleitung

Steigerung der körperlichen Leistungsfähigkeit durch physiologische Adaptionen (z.B. Mitochondriale Biogenese, Proteinbiosynthese, verbesserte Kapillarisierung, Erhöhung der Anzahl an Erythrozyten etc. (Hottenrott & Neumann, 2010; Seiler & Kjerland, 2006)) hervorzurufen ist ein wesentliches Ziel von Training im Leistungs-, Breiten- und Gesundheitssport. Zur Indizierung von Adaptionen werden insbesondere die Reizdauer, -frequenz, -intensität in Abhängigkeit der jeweiligen Sportart und der Zielstellung des Sportlers vorgegeben. Ausgangspunkt für Planungen zu Vorgaben der Reizdauer, -frequenz, -intensität sind individuelle Vorerfahrungen zur Anpassung des Sportlers an frühere Trainingsprozesse und/oder die auf Gruppenmittelwerten basierende wissenschaftliche Evidenzlage zur Wirksamkeit verschiedener Trainingsvorgaben. Die grundlegende Struktur der Trainingsplanung basiert auf dem Superkompensations- sowie dem kybernetischen Modell.

Nach Theorie des Superkompensationsmodells wird angenommen, dass sich sämtliche biologische Systeme in Homöostase befinden. Trainingsinduzierte mechanische, metabolische, elektrische oder thermische Reize verursachen eine Störung der Homöostase auf molekularer und organsystemischer Ebene. Je nach Reizintensität, -dauer und -häufigkeit können tiefgreifende Störungen der Homöostase eintreten. Diese reichen von akuter Ermüdung, funktionellem und nicht funktionellem Übertraining, subklinischen Gewebeschäden, klinischen Symptomen, hin zu Verletzungen und/oder Krankheiten (Fry, Morton, & Keast, 1991; Soligard et al., 2016). Laut Superkompensationsmodell ist dieser Prozess reversibel und nach einer Erholungsphase kann nicht nur eine Homöostase wieder hergestellt, sondern eine gesteigerte Leistungsfähigkeit von Organsystemen erreicht werden (Fry et al., 1991; Soligard et al., 2016).

Aufbauend auf dem Modell der Superkompensation geht das kybernetische Modell davon aus, dass dieser Prozess mathematisch beschreibbar, vorhersagbar und damit zielgenau planbar ist (Andreas Hohmann, Lames, & Letzelter, 2002; Zaciorskij, 1971). Grundlage hierfür ist die Annahme, dass es einen streng funktionalen Zusammenhang zwischen Training, Erholung und molekularen bzw. organsystemischen akuten Reaktionen und chronischen Adaptionen gibt, welche zu Leistungsverbesserungen führen.

Das kybernetische Modell (und damit die darauf aufbauenden Trainingsvorgaben) bildet nur unvollständig den Prozess der Trainingsanpassung ab, da 1) aufgrund der Komplexität der ablaufenden Teilreaktionen und -adaptionen auf molekularer und organsystemischer Ebene diese kaum mathematisch beschreibbar sind und 2) inter- und intra-individuelle Differenzen nicht in dieses Modell einfließen (A Hohmann & Lames, 2002). Die Limitationen des kybernetischen Modells zur Erstellung von Trainingsvorgaben werden in der Praxis durch inter-individuelle Unterschiede in akuten Reaktionen, chronischen physiologischen Adaptionen (z. B. in der maximalen Sauerstoffaufnahme) und Leistungsverbesserungen deutlich (Joyner & Lundby, 2018; Zinner, Olstad, & Sperlich, 2018). Beispielhaft zeigt Abbildung 1 die prozentualen Veränderungen der maximalen Sauerstoffaufnahme bei verschiedenen Sportlern in Folge eines auf dem kybernetischen Modell erstellten vierwöchigen Ausdauertrainingsplans.

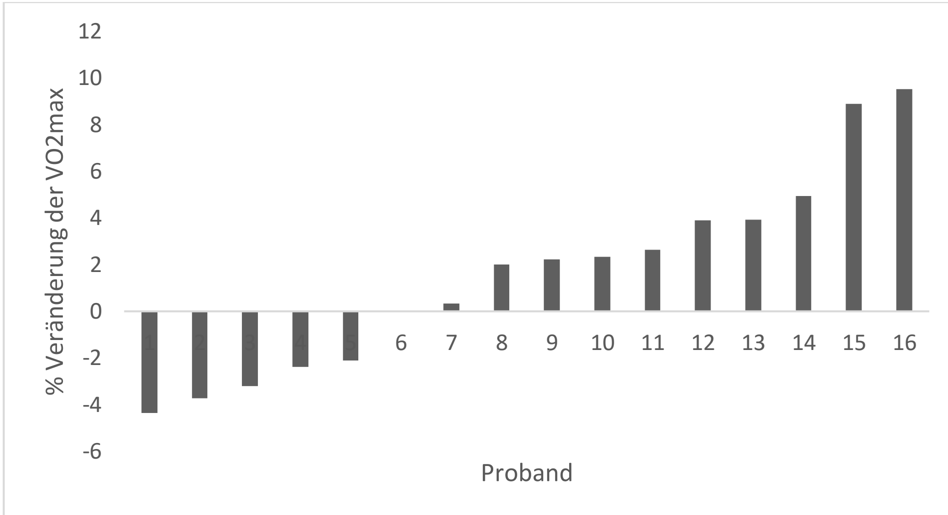


Abbildung 1: *Veränderungen der maximalen Sauerstoffaufnahme bei verschiedenen Probanden nach einem vordefinierten Trainingsplan (Düking, unveröffentlichte Daten).*

Gründe für die unterschiedlichen Adaptionen sind derzeitiger wissenschaftlicher Diskussionsgegenstand (Bacon, Carter, Ogle, & Joyner, 2013; Montero & Lundby, 2017; Tanaka, 2018). In der Vergangenheit wurde genetischen Faktoren ein hoher Stellenwert an den unterschiedlichen akuten Reaktionen und chronischen Adaptionen zugesprochen (Bouchard et al., 1999; Joyner & Lundby, 2018; Rankinen et al., 2016). In der neueren wissenschaftlichen Literatur findet sich jedoch vermehrte Evidenz, dass die chronischen Adaptionen und Leistungsverbesserungen unabhängig von genetischen Faktoren eher auf das individuelle Verhältnis von Trainingsbelastung und –beanspruchung zurückzuführen sind (Joyner & Lundby, 2018; Kiviniemi et al., 2010; Kiviniemi, Hautala, Kinnunen, & Tulppo, 2007; Montero & Lundby, 2017; Tanaka, 2018; Zinner et al., 2018). Trainingsbelastung ist definiert als Summe aller Trainings- und Leistungsanforderungen (Hottenrott & Neumann, 2010), engl. „external load") und Trainingsbeanspruchung als Inanspruchnahme körperlicher und psychischer Leistungsvoraussetzungen des Sportlers bei der Bewältigung von

Belastungen (Weineck, 2007), engl. „internal load“) (Bacon et al., 2013; Montero & Lundby, 2017; Tanaka, 2018).

Es ist bekannt, dass gleiche Belastung sowohl inter- als auch intraindividuell unterschiedliche Beanspruchung in Abhängigkeit diverser dynamischer Faktoren (z.B. Leistungsniveau, generelle Gesundheit, physische und/oder psychische Vorbelastung, Umweltbedingungen wie Temperatur oder Luftfeuchte etc.) hervorruft (Schwellnus et al., 2016; Soligard et al., 2016). Studien zeigen, dass bei individueller und situativer Anpassung von Trainingsprozessen an das individuelle Verhältnis von Belastung- bzw. Beanspruchung weniger inter-individuelle Unterschiede in physiologischen Adaptionen und Leistungsverbesserungen erreicht werden können als bei Trainingsvorgaben, welche auf dem kybernetischen Modell beruhen (Javaloyes, Sarabia, Lamberts, & Moya-Ramon, 2018; Javaloyes, Sarabia, Lamberts, Plews, & Moya-Ramon, 2019).

Trainingsvorgaben sollten nicht starr, sondern flexibel und als ein im zeitlichen Verlauf an das jeweilige individuelle Verhältnis zwischen Belastung und Beanspruchung angepasster Prozess verstanden werden (Düking, Achtzehn, Holmberg, & Sperlich, 2018; Schwellnus et al., 2016; Soligard et al., 2016). Hierzu werden eine engmaschige Erfassung, Analyse („Monitoring“) sowie kontextabhängige Interpretation von sportartspezifischen Belastungs- und Beanspruchungsmarkern im Training und Wettkampf benötigt (Schwellnus et al., 2016; Soligard et al., 2016). Auf Grundlange dieser Marker kann theoretisch eine Einschätzung über die Zeit erfolgen, ob Trainingsprozesse anhand der jeweiligen situativen Balance zwischen Belastung und Beanspruchung angepasst werden sollten. Für das Monitoring von Belastungs- und Beanspruchungsmarkern müssen die verwendeten diagnostischen Methoden und Techniken, um in der Praxis angewendet zu werden, verschiedene Kriterien erfüllen. Zu den wesentlichen Kriterien gehören z. B. die non- oder minimal-invasive

Erfassung von wesentlichen physiologischen Belastungs- und Beanspruchungsmarkern (z.B. zurückgelegte Distanz in verschiedenen Geschwindigkeitszonen, Herzfrequenz), eine einfache (laienhafte) Handhabung der Messtechnik mit zeitnaher/unmittelbarer Ergebnisrückmeldung sowie eine ausreichende Reliabilität und Validität der bereitgestellten Marker für die Trainingspraxis (Schwellnus et al., 2016; Starling & Lambert, 2017).

In der Vergangenheit konnte keine Messtechnik oder Methodik diese Kriterien ausreichend erfüllen. Eine individualisierte und situative Anpassung des Trainingsprozesses war nur sehr umständlich und eingeschränkt möglich.

Getrieben durch immer schneller voranschreitende technologische Entwicklungen (beispielsweise durch die Erhöhung der Anzahl vorhandener Transistoren auf einem Mikroprozessor) können miniaturisierte Sensoren größere Rechenleistungen erzielen (Moore, 1965; Waldrop, 2016). Sensorik, welche zeiteffizient und non-invasiv verschiedenste Belastungs- und/oder Beanspruchungsparameter verschiedener Organsysteme erfasst, analysiert und im Sinne eines Biofeedbacks zurückmeldet, kann heutzutage komfortable am Körper getragen werden (Düking, Holmberg, & Sperlich, 2017). Im englischen wird diese tragbare Sensorik als „Wearable Sensor Technology“ oder „Wearables“ zusammengefasst. Durch den schnellen technologischen Fortschritt wurde es nötig, eine bis dahin im Sport sowie in der trainingswissenschaftlichen Forschung kaum existierende Produktkategorie mit der Bezeichnung „Wearable/Wearable Technology“ verstärkt zu etablieren (Duden, 2020; Düking, Hotho, Holmberg, Fuss, & Sperlich, 2016). Zwar ist die Verwendung verschiedener Wearables zur Erfassung von Körpersignalen, welche als Belastungs- und/oder Beanspruchungsmarker interpretiert und zur individualisierten Steuerung von Trainingsprozessen herangezogen werden keine neue Erscheinung, die Anzahl der kontinuierlich messbaren Belastungs- und/oder Beanspruchungsmarker genau wie die

Anzahl kommerziell erhältlicher Wearables steigt jedoch rapide (Abbildung 2). Kommerziell erhältliche Wearables, welche für den Einsatz von Sportler/innen zum Monitoring von Belastungs- und/oder Beanspruchungsmarker und zur individualisierten Steuerung von Trainingsprozessen vermarktet werden, lassen sich anhand ihres Trageorts als sogenannte „Wristables", „Smart Clothes", „Hearables" oder „Ear-Worn Devices", „Smart Patches" oder „Smart Glasses" kategorisieren.

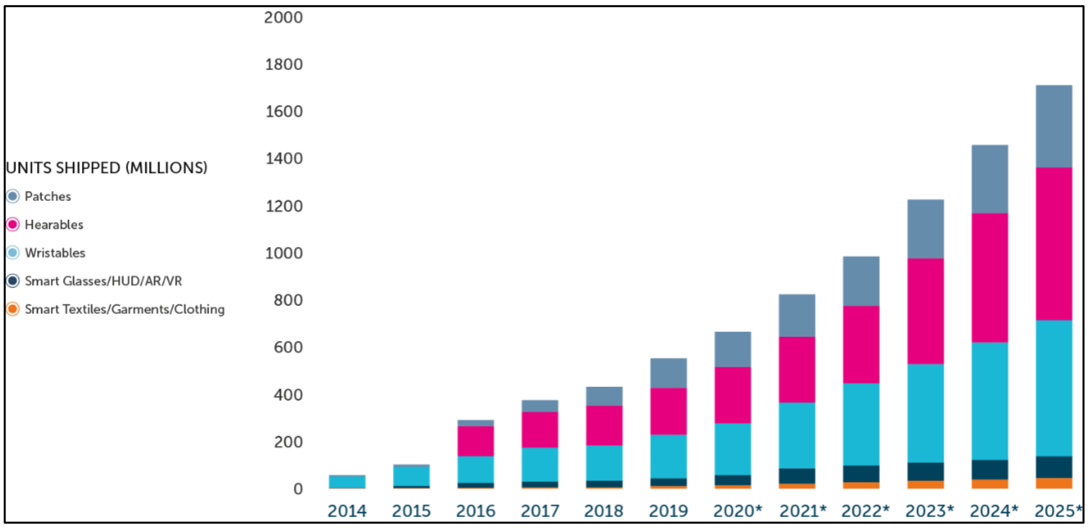


Abbildung 2: *Anzahl verkaufter Wearables weltweit. *: Antizipierte Verkaufszahlen (Abgedruckt mit Erlaubnis von WT | Wearable Technologies AG).*

In der Forschung wird die Relevanz von Wearables durch den Anstieg an Publikationen in wissenschaftlichen Fachzeitschriften deutlich. Im Jahr 2015 wurden lediglich 33 Artikel in der größten biomedizinischen Datenbank Pubmed.gov zu den Begriffen „Wearable Technology Sport" veröffentlicht, im Jahr 2019 bereits 256 Artikel (Abbildung 3).

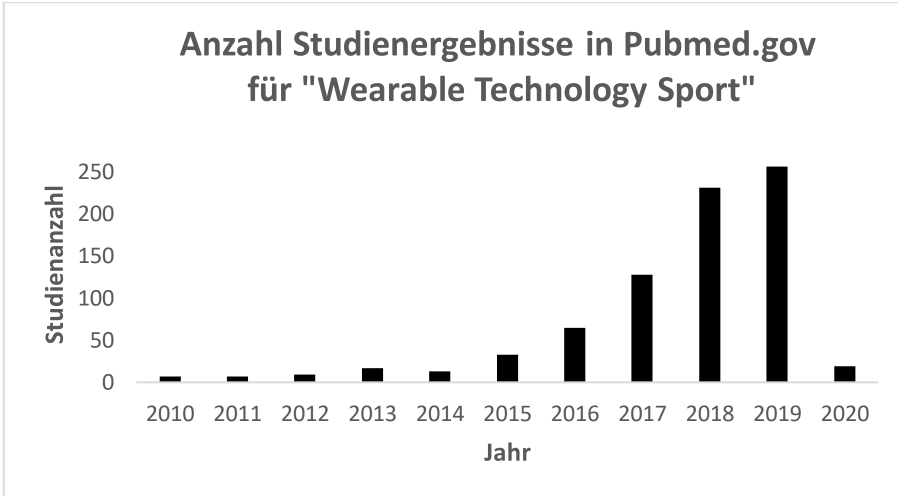


Abbildung 3: *Anzahl jährlicher Veröffentlichungen zum Themengebiet "Wearable Technology Sport" in der größten biomedizinischen Fachdatenbank Pubmed.gov von 01.01. 2010 bis zum 31.1.2020*

In der sportlichen Praxis wird die Relevanz von Wearables belegt z.B. durch Dachorganisationen wie das American Colleague of Sports Medicine, die World Athletics Organisation (früher IAAF) und die FIFA. Das American Colleague of Sports Medicine veröffentlicht jährliche Fitnesstrends, in welcher Wearables seit 2016 Spitzenplatzierungen belegen (Thompson, 2015, 2016, 2018). Vor 2016 waren Wearables in diesen Trends nicht gelistet. Organisationen wie die World Athletics Organisation oder die FIFA erlauben mittlerweile den Einsatz von Wearables während Wettkämpfen und erkennen damit den Mehrwert von Wearables unter anderem zur individualisierten Steuerung von Trainingsprozessen an (Brud, 2015; IAAF, 2017).

Es bleibt zu klären, ob der technologische Fortschritt im Bereich Wearables dazu beitragen kann, Belastungs- und/oder Beanspruchungsmarker reliabel und valide zu erfassen, zu analysieren und ob diese Marker zur individualisierten Steuerung von Trainingsprozessen verwendet werden können.

Übergeordnetes Ziel der vorliegenden kumulativen Dissertation war es, den Einsatz von Wearables zum Monitoring von Belastungs- und/oder Beanspruchungsmarkern zur individualisierten Steuerung von Trainingsprozessen aus physiologisch-trainingswissenschaftlicher Perspektive zu untersuchen und zu bewerten.

In den letzten Jahren verschiedene Studien durchgeführt und in einschlägigen wissenschaftlichen Fachzeitschriften veröffentlicht (summierter Impact-Faktor: 20.88).

Im gegebenen Kontext befasst sich *Studie 1* mit von Wearables relevanten und potenziell erfassbaren Markern zur individualisierten Steuerung von Trainingsprozessen.

Ausgehend von den Ergebnissen aus *Studie 1* werden in *Studie 2* Empfehlungen zur Evaluierung von Wearables im Hinblick auf deren Reliabilität, Sensitivität und Validität im trainingspraktischen Kontext ausgesprochen. Diese Empfehlungen werden in *Studie 3* aufgegriffen und es werden verschiedene Wearables im Hinblick auf ihre Validität bei verschieden Laufintensitäten getestet. Laufen wurde hier als exemplarisches Modell gewählt, da in vielen Sportarten unterschiedliche Laufintensitäten vorkommen.

Die durchgeführte systematische Literaturrecherche in *Studie 4* befasst sich mit dem Vergleich von vordefiniertem und datenbasiert-gesteuertem Training auf Leistungsmarker sowie physiologischen Anpassungserscheinungen im Laufsport.

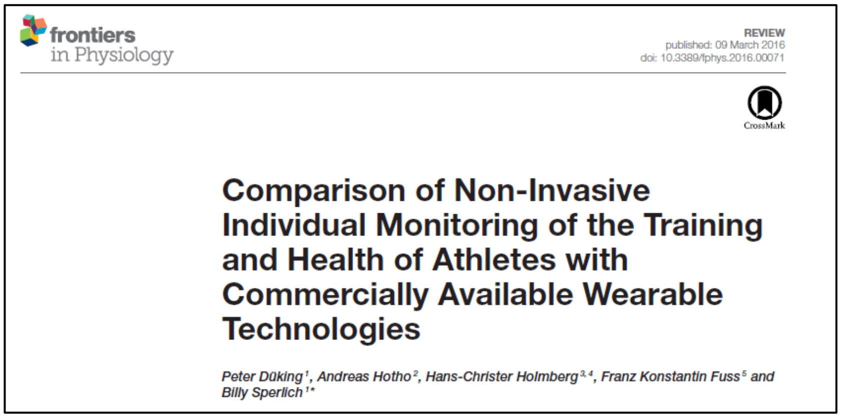
Da kein derzeitig erhältliches Wearable alle oder zumindest eine Vielzahl an relevanten Markern erfassen kann, wurde in *Studie 5* ein Rahmenmodell zum Einsatz von Wearables zur individualisierten Steuerung von Trainingsprozessen dargelegt.

Studie 6 hatte das Ziel Faktoren zu identifizieren, die notwendig sind, damit Wearables zum Monitoring verschiedener Belastungs- und/oder Beanspruchungsmarker zur individualisierten Steuerung von Trainingsprozessen Anwendung finden.

Der weitere Aufbau der vorliegenden Dissertation gliedert sich in einer prägnanten Zusammenfassung der wichtigsten Ergebnisse der jeweiligen Studien 1 bis 6 sowie einer abschließenden Diskussion.

2. Einzelstudien

2.1. **Studie 1:** Düking P, Hotho, A, Holmberg HC, Fuss FK, Sperlich B. (2016). **Comparison of Non-Invasive Individual Monitoring of the Training and Health for Athletes with commercially available Wearable Technologies**. *Front Physiol*. 7:71



frontiers in Physiology

REVIEW
published: 09 March 2016
doi: 10.3389/fphys.2016.00071

Comparison of Non-Invasive Individual Monitoring of the Training and Health of Athletes with Commercially Available Wearable Technologies

*Peter Düking[1], Andreas Hotho[2], Hans-Christer Holmberg[3,4], Franz Konstantin Fuss[5] and Billy Sperlich[1]**

In der trainingswissenschaftlichen Literatur gibt es eine Vielzahl von Belastungs- und Beanspruchungsmarkern, welche je nach Sportart potentiell zur individualisierten Steuerung von Trainingsprozessen verwendet werden können (Halson, 2014). *Studie 1* untersuchte, welche Marker non-invasiv mit kommerziell erhältlichen Wearables mit entsprechender Sensorik erfasst werden können. In *Studie 1* wurde der Fokus auf kommerziell erhältliche Wearables gelegt, da Sportreibende nur selten Zugriff auf Wearables im wissenschaftlichen Entwicklungsstadium haben, wodurch deren Anwendung deutlich limitiert ist. Weiter wurde sich auf non-invasive Marker beschränkt, da invasive Techniken zur Erhebung der Marker (bspw. kapillare Blutentnahmen zur Bestimmung von Kreatinkinase) in der Sportpraxis ein engmaschiges Monitoring zur individualisierten Steuerung von Trainingsprozessen erschweren oder verhindern (Düking et al., 2016).

Die in *Studie 1* enthaltenen Grafiken 1, 2 und 3 fassen die derzeitigen Wearables in diesen Kategorien zusammen. Zum Zeitpunkt der *Studie 1* gab es n = 22 Wristables, n = 8 Smart Clothes, sowie n = 4 Hearables und n = 3 sonstige Wearables (z. B. am Oberarm getragene Geräte).

Von den Herstellern werden Wearables vermarktet welche laut Marketingbotschaften viele Marker erfassen können. Die laut Herstellerangaben am häufigsten erfassbaren Marker mit den ausgewählten Wearables sind in absteigender Reihenfolge: die Herzfrequenz (n = 30), Dauer der Trainingseinheit (n = 28), zurückgelegte Distanz (n = 22), Geschwindigkeit (n = 16), Schlafdauer und/oder -qualität (n = 14), Höhenlage (n = 11), Herzfrequenzvariabilität (n = 5), Herzfrequenzerholung (n = 3), Blutoxygenierung (n = 3), neuromuskulärer Ermüdung (n = 2), Laktatschwellen (n = 1), UV-Strahlung (n = 1), Körpertemperatur (n = 1) und Umgebungstemperatur (n = 1).

Von den 37 in *Studie 1* identifizierten Wearables wurden lediglich neun, im Hinblick auf Reliabilität und/oder Validität einiger bereitgestellten Marker mit unterschiedlichen Ergebnissen, wissenschaftlich evaluiert. Beispielsweise wurde die Validität und/oder Reliabilität der Herzfrequenz in Ruhe und/oder unter Belastung bei drei Wearables untersucht. Der BioHarness™ 3 (Biopac Systems, Inc., Goleta, Vereinigte Staaten von Amerika) wurde mit einer akzeptablen Validität und Reliabilität ($r = \sim 0.91$, $p < 0.01$; $CV\% < 7.6$) bewertet, welche jedoch bei steigender Bewegungsgeschwindigkeit abnehmen (Johnstone, Ford, Hughes, Watson, & Garrett, 2012a, 2012b). Bei der Mio Alpha© (Mio Labs Inc., Portland, Vereinigte Staaten von Amerika) wich die Herzfrequenz beim Gehen (2.41 ± 3.99 bpm, $p < 0.05$), Gewichtheben (23.30 ± 31.94 bpm, $p < 0.01$), sowie Radfahren (3.26 ± 11.38 bpm, $p < 0.05$) signifikant von den Ergebnissen des Referenzgeräts ab (Spierer, Rosen, Litman, & Fujii, 2015). Der Polar V800 (Polar Electro Oy, Kempele, Finnland) konnte eine valide Bestimmung bei der Erkennung von R-R-Intervallen des Herzschlags unter Ruhebedingungen bescheinigt werden (ICC > 0.99, Error: 0.09 %) (Giles, Draper, & Neil, 2016).

Zusammenfassend zeigte *Studie 1*, dass

1) einige, aber nicht alle Belastungs- und/oder Beanspruchungsmarker mithilfe von Wearables erfasst werden können. Es gibt für einige Marker (wie z. B. Kreatinkinase, Cortisol oder Testosteron) noch keine miniaturisierte und/oder non- oder zumindest minimalinvasive Technologie, die in Wearables angewendet werden kann. Für weitere Marker (z. B. Luftfeuchte, Hydrationsstatus, neuromuskuläre Ermüdung oder subjektive Marker, wie zum Beispiel das subjektive Belastungsempfinden oder die „Akute-Erholungs-und-Stress-Skala“ (Belbasis & Fuss, 2018; A. Belbasis, F. K. Fuss, & J. Sidhu, 2015b; Borg, 1970; Nassi, Ferrauti, Meyer, Pfeiffer, & Kellmann, 2017)), stehen miniaturisierte Technologien und/oder Algorithmen zur Verfügung. Diese werden aber derzeit nicht in Wearables verbaut,
2) die Mehrheit der kommerziell erhältlichen Wearables und deren zur Verfügung gestellte Marker im Hinblick auf deren Reliabilität und/oder Validität während sportspezifischer Bewegungen und Intensitäten nicht wissenschaftlich untersucht sind,
3) sich trotz gleicher Sensorik große Unterschiede in der Reliabilität und/oder Validität der Wearables zeigen,
4) evaluierende Studien heterogene Test- und Auswerteprotokolle, inklusive verschiedener statistischer Parameter sowie Begrifflichkeiten verwenden, wodurch der Vergleich von Wearables erschwert wird,
5) derzeit kein Wearable alle aus technologischer Perspektive möglichen Marker mit ausreichender Reliabilität und Validität erfasst. Dementsprechend bräuchte man zum

Monitoring, je nach Sportart, mehrerer Wearables zur aussagekräftigen Trainingssteuerung. Folglich wird zukünftig ein System, bestehend aus verschiedenen Wearables (und ggf. weiteren Technologien) benötigt, welches ein Monitoring relevanter Marker reliabel und valide ermöglicht, um Trainingsprozessen individualisiert steuern zu können.

2.2. **Studie 2:** Düking P, Fuss FK, Holmberg HC, Sperlich B. (2018). **Recommendations for assessment of the reliability, sensitivity and validity of data provided by wearables sensors designed for monitoring physical activity**. *JMIR Mhealth Uhealth*;6(4):e102

JMIR MHEALTH AND UHEALTH Düking et al

Viewpoint

Recommendations for Assessment of the Reliability, Sensitivity, and Validity of Data Provided by Wearable Sensors Designed for Monitoring Physical Activity

Peter Düking[1,2*], MSc; Franz Konstantin Fuss[3*], MD, PhD; Hans-Christer Holmberg[2,4,5*], PhD; Billy Sperlich[1*], PhD

In *Studie 1* wurde deutlich, dass

1) wenige kommerziell erhältliche Wearables auf ihre Reliabilität und/oder Validität hin untersucht worden sind und
2) einzelne Evaluationsstudien heterogene Test- und Auswerteprotokolle inklusive verschiedener statistischer Parameter verwenden.

Dadurch wird der Vergleich von Wearables im Hinblick auf die Reliabilität und/oder Validität und damit auch die individualisierte Steuerung von Trainingsprozessen erschwert. Um die Planung und Durchführung von wissenschaftlichen Evaluationsstudien von Wearables im sportlichen Kontext zu beschleunigen, zu vereinheitlichen und um die Vergleichbarkeit von Wearables zu fördern, wurden in *Studie 2* Empfehlungen zur Durchführung ebendieser Studien formuliert und veröffentlicht.

Abbildung 4 fasst die wesentlichen Aspekte, welche Berücksichtigung finden sollten, zusammen.

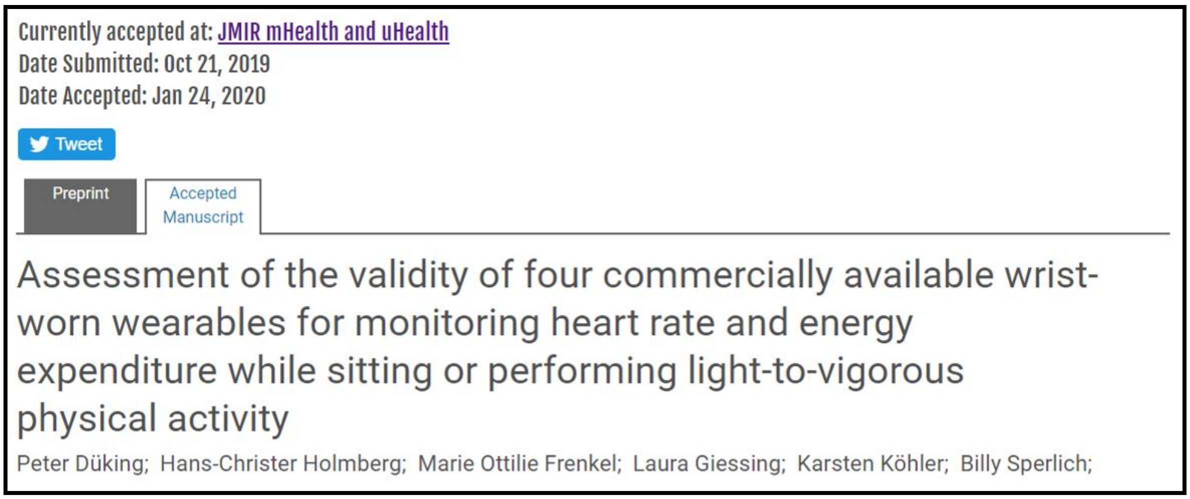
Table 1. Checklist of important considerations associated with the evaluation of data provided by wearables.

Factor	Action/recommendation
Sensor characteristics	• Scrutiny of each sensor
Software	• Specify calculations/algorithms • Report the version of software and firmware involved
Raw data	• Report sampling frequency • Report filtering techniques and aggregation
Durability	• Report the durability and age of the device
Anatomical positioning	• Report the precise anatomical positioning of sensors • Report signal reproducibility upon repeated putting on and taking off • Report considerations concerning positioning • Control for and describe potential interference
Study population	• Describe the target population • Specify inclusion and exclusion criteria • Generalize to other populations only with great care
Exercise protocol	• Describe conditions (eg, ambient temperature, altitude) in as much detail as possible • Investigate different forms of exercise (running, cycling, walking, moving freely) • Apply different intensities (lying, sitting, low and high intensity)
Confounders	• Report any potential confounding factors • Perform assessment in both controlled and real-life scenarios • Check for potential crosstalk between devices
Assessment of reliability	• Determine intradevice and interdevice reliability • Document intrasubject standard deviation • Report the coefficient of variation • Calculate the intraclass correlation coefficient • Recruit at least 50 participants • Report systematic bias
Assessment of sensitivity	• Calculate the smallest worthwhile change
Assessment of validity	• Choose an appropriate criterion measure and assess the reliability of this measure as well • Perform linear regression analysis • Calculate Pearson's product-moment correlation

Abbildung 4: *Checkliste zur Berücksichtigung bei Reliabilitäts- und/oder Validitätsstudien von Markern bereitgestellt durch Wearables (abgedruckt mit Erlaubnis von: JMIR mHealth and uHealth)*

Diese Checkliste wurde für Wearables im Generellen, und nicht im Hinblick auf eine spezielle Sensorik, Sportart und/oder Algorithmus entwickelt. Im Einzelfall kann es sinnvoll sein, andere methodologische Überlegungen anzustellen.

Studie 3: Düking P, Holmberg HC, Frenkel MO, Giessing L, Köhler K, Sperlich B. (2020). **Assessment of the validity of four commercially available wrist-worn wearables for monitoring heart rate and energy expenditure while sitting or performing light-to-vigorous physical activity.** *JMIR mHealth and uHealth*. preprint



Currently accepted at: JMIR mHealth and uHealth
Date Submitted: Oct 21, 2019
Date Accepted: Jan 24, 2020

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Assessment of the validity of four commercially available wrist-worn wearables for monitoring heart rate and energy expenditure while sitting or performing light-to-vigorous physical activity

Peter Düking; Hans-Christer Holmberg; Marie Ottilie Frenkel; Laura Giessing; Karsten Köhler; Billy Sperlich;

Ziel der *Studie 3* war es, die Beanspruchungsmarker Herzfrequenz und Energieverbrauch aktueller High-End-Wearables von Herstellern, die in Masse von Sportlern/innen genutzt werden, mit dem jeweiligen Goldstandard-Messinstrument im Hinblick auf deren Validität im Sitzen sowie bei verschiedenen Laufintensitäten zu untersuchen. Das Studiendesign sowie die statistische Analyse und Interpretation orientierte sich an den Empfehlungen aus *Studie 3*. Die ausgewählten Wearables waren Apple Watch Series 4, Version 5.1 (Apple Inc., Cupertino, CA, USA); Polar Vantage V, Firmware: 3.1.7 (Polar Electro Oy, Kempele, Finland); Garmin Fenix 5, Software 7.6 (Garmin, Olathe, KS, USA); und Fitbit Versa Version 32.33.1.30 (Fitbit Inc., San Francisco, CA, USA). Alle Wearables verwendeten Photoplethysmographie zur Messung der Herzfrequenz am Handgelenk. Unter Verwendung welcher Sensordaten und Algorithmen der Energieverbrauch errechnet wird, wird von keinem Hersteller bekannt gegeben.

Zur Überprüfung der Validität wurden 25 Athleten an zwei Testtagen mit jeweils zwei Wearables ausgestattet. Die Athleten saßen für fünf Minuten und liefen bei verschiedenen Geschwindigkeiten (1.1, 1.9, 2.7, 3.6, 4.1 m/s) auf einem Laufband. Zudem vollführten die Athleten ein wiederholtes multidirektionales Sprintprotokoll (6 x 15 Sekunden, unterbrochen durch 15-sekündige Pausen). Als Referenzgeräte für die Herzfrequenz diente ein Polar H7 Brustgurt, welcher häufig für diese Art von Studien verwendet wird (Wahl, Düking, Droszez, Wahl, & Mester, 2017). Als Referenzgerät für den Energieverbrauch diente eine portable Einzelatemzuganalyse (Metamax 3B, CORTEX Biophysik GmbH, Leipzig, Germany), welche reliabel ventilatorische und metabolische Marker erfasst und welche bereits in ähnlichen Studien verwendet wurde (Vogler, Rice, & Gore, 2010; Wahl et al., 2017).

Für die Erfassung der Herzfrequenz bei verschiedenen Geschwindigkeiten betrug der standardisierte typische Fehler 0.09-0.62, 0.13-0.88, 0.62-1.24 und 0.47-1.94 für die Apple Watch, Polar Vantage V, Garmin Fenix 5 bzw. Fitbit Versa. Je nach Geschwindigkeit lagen die entsprechenden Varianzkoeffizienten (CV%) zwischen 0.9 und 4.3%, zwischen 2.2 und 6.7%, zwischen 2.9 und 9.2% und zwischen 4.1 und 19.1%.

Abbildungen 5 und 6 zeigen den standardisierten typischen Fehlerwert für die Herzfrequenz sowie für den Energieverbrauch verschiedener Wearables bei verschiedenen Laufgeschwindigkeiten.

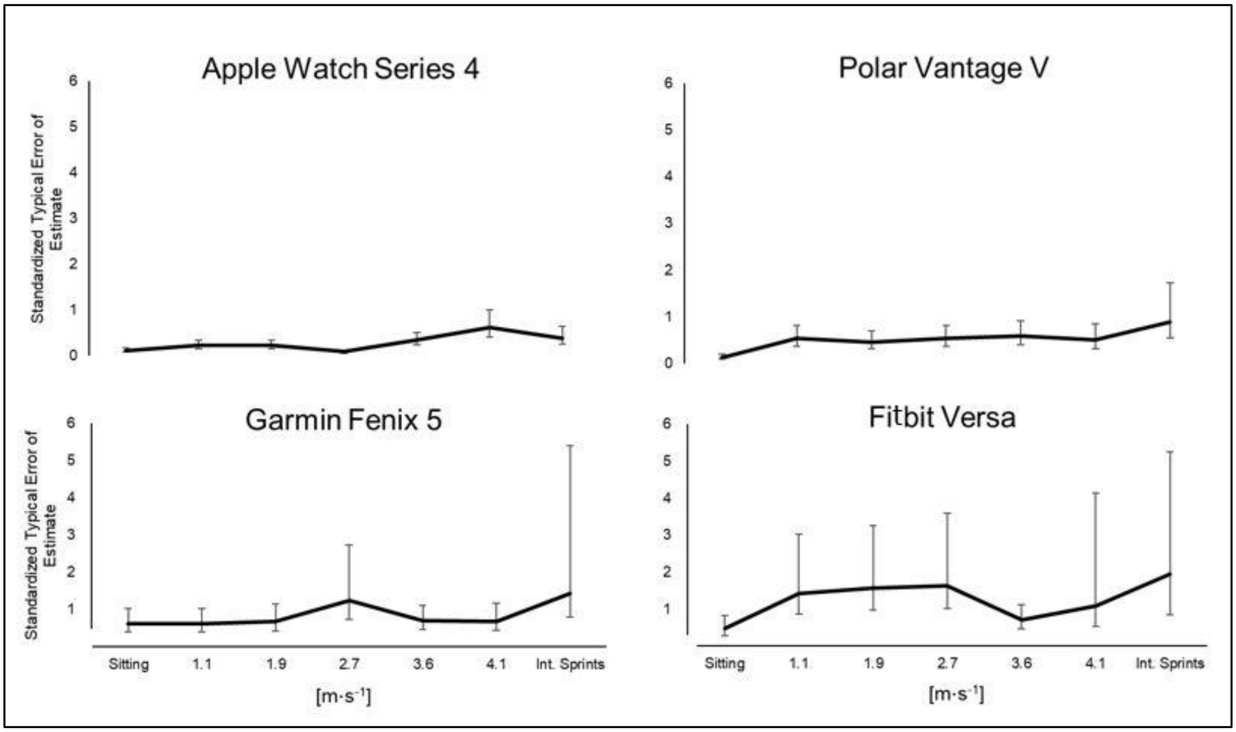

Abbildung 5: *Standardisierter typischer Fehler (90% Konfidenzintervall) für den Beanspruchungsmarker Herzfrequenz erhoben mit verschiedenen Wearables während „Sitzen“ und verschiedenen Laufgeschwindigkeiten (abgedruckt mit Erlaubnis von: JMIR mHealth and uHealth)*

Für die Erfassung des Energieverbrauchs bei verschiedenen Laufgeschwindigkeiten betrug der standardisierte typische Fehler 0.34-1.84, 0.32-1.33, 0.46-4.86, 0.41-1.65 für die Apple Watch, Polar Vantage V, Garmin Fenix 5 bzw. Fitbit Versa. Abhängig von der Laufgeschwindigkeit lag der entsprechende CV% zwischen 13.5 und 27.1 %, zwischen 16.3 und 28.0 %, zwischen 15.9 und 34.5 % und zwischen 8.0 und 32.3 %.

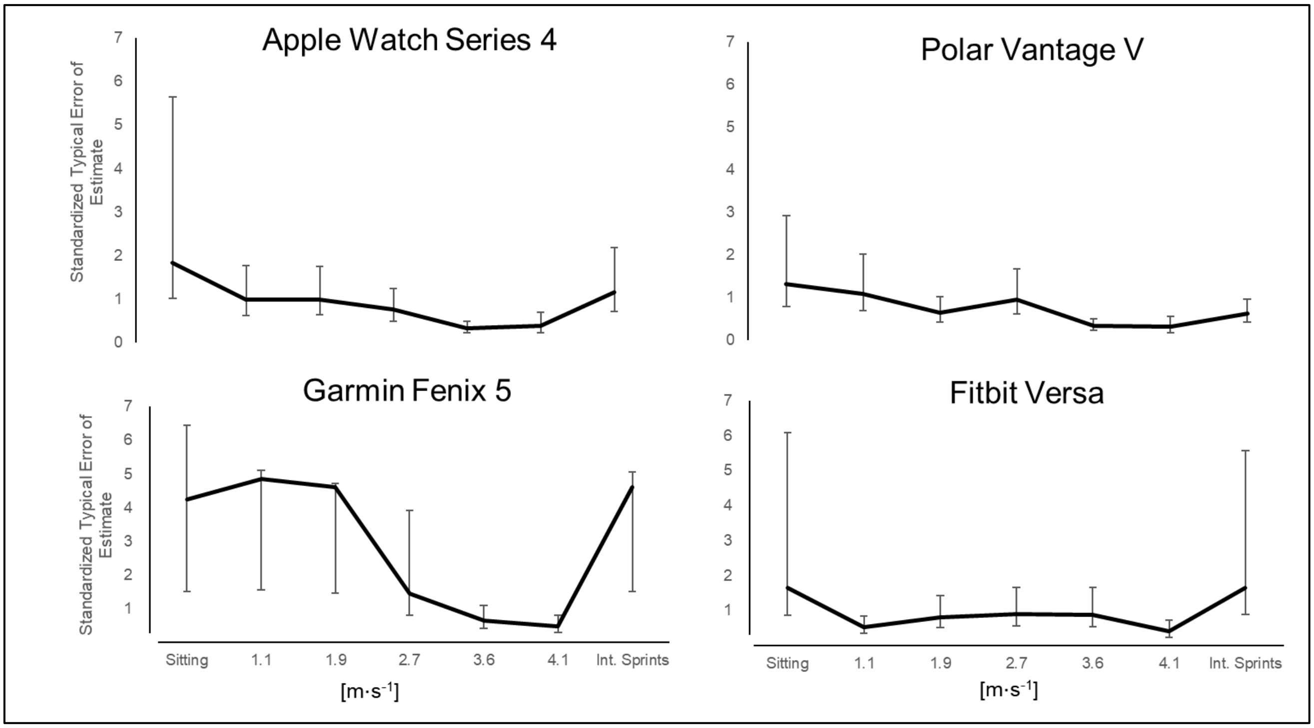

Abbildung 6: *Standardisierter typischer Fehler (90% Konfidenzintervall) für den Beanspruchungsmarker Energieverbrauch erhoben mit verschiedenen Wearables während „Sitzen“ und verschiedenen Laufgeschwindigkeiten (abgedruckt mit Erlaubnis von: JMIR mHealth and uHealth)*

Zusammenfassend zeigt *Studie 3*, dass

1) die Apple Watch Series 4 die beste Validität bei der Messung der Herzfrequenz im Sitzen oder bei verschiedenen Laufintensitäten aufweist,
2) sowohl die Apple Watch und Polar Vantage V sich zur gültigen Erfassung der Herzfrequenz bei den getesteten Laufgeschwindigkeiten eignen. Die Herzfrequenzdaten der Garmin Fenix 5 und Fitbit Versa sollten mit Vorsicht interpretiert werden, da bei bestimmten Laufgeschwindigkeiten eine geringe Validität nachgewiesen wurde,
3) keines der vier am Handgelenk getragenen Wearables zur Überwachung des Energieverbrauchs bei den getesteten Laufgeschwindigkeiten verwendet werden sollte.

Nach aktuellem Kenntnisstand ist die durchgeführte *Studie 3* die erste Studie, welche die genannten Modelle im Hinblick auf die Validität der Herzfrequenz und des Energieverbrauchs bei verschiedenen Geschwindigkeiten evaluiert. Der Vergleich der vorliegenden Ergebnisse mit früheren Modellen der einzelnen Hersteller könnte jedoch Aufschluss darüber geben, ob Modelle von Herstellern tendenziell reliable und/oder valide Marker zur Verfügung stellen. Dies muss jedoch vorsichtig erfolgen, da nicht bekannt ist, ob die Sensoren und/oder Algorithmen von Herstellern geändert wurden. Vergleicht man dennoch die vorliegenden Ergebnisse der *Studie 3* mit Ergebnissen aus bestehender Literatur, geht hervor, dass die am Handgelenk getragenen Wearables von Apple Inc. und Polar Electro Oy, gefolgt von den Wearables von Garmin oder Fitbit Inc, die höchste Validität für die Messung der Herzfrequenz bei verschiedenen Aktivitäten aufweisen (Boudreaux et al., 2018; Dooley, Golaszewski, & Bartholomew, 2017; Thomson et al., 2019).

2.4. Studie 4: Düking P, Zinner C, Reed JL, Holmberg HC, Sperlich B. (2020). **Predefined vs. data guided training prescription based on autonomic nervous system variation: A systematic review.** *Scand J Med Sci Sports* (submitted, 26.02.2020)

Predefined vs. data guided training prescription based on autonomic nervous system variation: A systematic review

Peter Düking[1], Christoph Zinner[2], Jennifer L. Reed, [3-5], Hans-Christer Holmberg[6,7], Billy Sperlich[1]

Die Herzfrequenzvariabilität (engl. Heartratevariability, HRV) ist ein Marker, welcher in *Studie 1* als potenzieller Belastungsmarker zur individualisierten Steuerung von Trainingsprozessen identifiziert wurde und mit Wearables erfassbar ist.

Die HRV (definiert als zeitliche Differenz zwischen zwei zeitlich aufeinanderfolgenden R-R Zacken im Elektrokardiogramm) spiegelt die parasympathische und sympathische Aktivität des autonomen Nervensystems (ANS) wider. Da eine individuell höhere als normale Beanspruchung und/oder eine Beeinträchtigung der Erholung mit einer Verringerung der HRV, und eine erhöhte Leistungsbereitschaft mit einem Anstieg der HRV verbunden ist (Nuuttila, Nikander, Polomoshnov, Laukkanen, & Hakkinen, 2017; Plews, Laursen, Stanley, Kilding, & Buchheit, 2013), kann die HRV theoretisch zur individualisierten Steuerung von Trainingsprozessen genutzt werden (Martinmaki & Rusko, 2008; Singh et al., 2018; Stanley, Peake, & Buchheit, 2013).

Ziel der *Studie 4* war es, mithilfe einer systematischen Literaturrecherche einen Vergleich zwischen einem vordefinierten und einem auf Grundlage der HRV individualisiert-gesteuerten Trainingsprozess im Hinblick auf physiologische Adaptionen und/oder Leistungsverbesserungen beim Läufer anzustellen.

Dazu wurde im Juli 2019 eine systematische Suche in den elektronischen Datenbanken PubMed, SPORTDiscus und Web of Science mit Stichwörtern in Bezug auf Ausdauer, Laufen, autonomes Nervensystem, Herzfrequenzvariabilität sowie Training durchgeführt. Studien wurden nur dann zur Analyse herangezogen, wenn sie

1) Interventionen umfassten, die überwiegend aus Lauftraining bestanden,
2) eine mindestens dreiwöchige Interventionsphase beinhalteten,
3) die Laufleistung und/oder physiologische Adaptionen vor und nach der Intervention analysierten,
4) eine Interventionsgruppe beinhalteten, welche ihr Training situativ an Veränderungen der HRV angepasst hat,
5) eine Kontrollgruppe hatten, welche ein vordefiniertes Training absolvierte und
6) gesunde und verletzungsfreie Läufer als Stichprobe hatten.

Insgesamt konnten fünf Studien mit sechs Interventionen und 166 Teilnehmern in die Ergebnisse der systematischen Literaturrecherche eingebunden werden. Vier dieser HRV-basierten Interventionen reduzierten die Anzahl an moderatem und/oder intensivem Training signifikant. In fünf Interventionen waren die Verbesserungen der Leistungsparameter (z. B. mittlere Geschwindigkeit ($km \cdot h^{-1}$) für einen 3000 m-Lauf, Zeit für einen 5000 m-Lauf, gelaufene Zeit auf der höchsten Stufe eines Stufentests ausgeführt auf einem Laufband) nach einem HRV-basierten Training größer als nach vordefiniertem

Training. Die maximale Sauerstoffaufnahme und submaximale Laufparameter (z. B. Laufgeschwindigkeit ($km \cdot h^{-1}$)) an einer Laktatschwelle verbesserten sich nach HRV-basiertem und vordefiniertem Training, ohne dass ein deutlicher Unterschied in der Verbesserung der maximalen Sauerstoffaufnahme bestand. Submaximale Laufparameter verbesserten sich nach einem HRV-basierten Training tendenziell stärker als nach einem vordefinierten Training.

Da erst fünf Studien zur individualisierten Steuerung von Trainingsprozessen beim Läufer durchgeführt wurden, besteht weiterer Forschungsbedarf. In *Studie 4* wurden daher Empfehlungen zur Durchführung zukünftiger Studien mit HRV-Steuerung erarbeitet. Insbesondere sollte zukünftige Forschung

1) evaluieren, ob die Veränderungen der HRV wirklich aufgrund des Trainings hervorgerufen worden sind, oder beispielsweise durch beruflichen oder sozialen Stress,
2) mithilfe kontrollierter Crossover-Studien intraindividuelle Unterschiede zwischen HRV-basiertem Training und vordefiniertem Training auf physiologische Adaptionen und Leistungsveränderungen zu untersuchen,
3) untersuchen, welche situativen Anpassungen der Trainingsvorgaben (bspw. eine Reduktion der Reizintensität, Applikation von Regenerationsmaßnahmen wie Kaltwasserimmersionen o.ä.) aufgrund Veränderungen der HRV den größten Effekt auf Leistungs- und/oder physiologische Adaptation haben und
4) den Einsatz weiterer Sensorik (insbesondere Photoplethysmographie) zur Bestimmung der HRV (bzw. Pulsratenvariabilität) erforschen, da diese Technologie einer in der Praxis höhere Compliance als die Erfassung der HRV erwarten lässt.

2.5. Studie 5: Düking P, Achtzehn S, Holmberg HC, Sperlich B (2018). **Integrated Framework of Load Monitoring by a Combination of Smartphone Applications, Wearables and Point-of-Care Testing Provides Feedback that Allows Individual Responsive Adjustments to Activities of Daily Living.** *Sensors (Basel).* 19;18(5)

sensors

MDPI

Article

Integrated Framework of Load Monitoring by a Combination of Smartphone Applications, Wearables and Point-of-Care Testing Provides Feedback that Allows Individual Responsive Adjustments to Activities of Daily Living

Peter Düking [1,*], Silvia Achtzehn [2,3], Hans-Christer Holmberg [4,5] and Billy Sperlich [1]

In *Studie 1* wurde deutlich, dass ein einziges Wearable nicht alle Belastungs- und Beanspruchungsmarker erfassen kann, die zur sportartspezifischen und individualisierten Steuerung von Trainingsprozessen relevant sind. *Studie 4* zeigt, dass es erste wissenschaftliche Evidenz gibt, dass der Marker HRV bei korrekter Erfassung mithilfe von Wearables und Interpretationen zur individualisierten Steuerung von Trainingsprozessen genutzt werden kann. Weiter wurde in *Studie 4* deutlich, dass weiterer Forschungsbedarf besteht, da unter anderem nicht klar ist, ob Veränderungen der HRV wirklich aufgrund des Trainings oder aufgrund anderer Faktoren hervorgerufen wurden. Eine Erforschung der Gründe der Veränderung der HRV könnte der weiteren individualisierten Steuerung von Trainingsprozessen dienen. Hierzu könnte (wie auch in *Studie 1* festgehalten) ein System aus verschiedenen Wearables und weiteren Datenquellen, welche verschiedenste Belastungs- und/oder Beanspruchungsmarker kontinuierlich erfassen, dienlich sein. Für die Praxis muss ein solches System zeiteffizient, so minimal-invasiv wie möglich und einfach handhabbar sein (Starling & Lambert, 2017). Neben tragbarer und non-invasiver Sensorik erscheinen aus dieser Perspektive Smartphone-Applikationen (Apps), sowie Point-of-Care-Testing-Geräte (POCT-Geräte) geeignet. Diese Gerätegruppen ermöglichen die non- oder minimalinvasive Erfassung einer Vielzahl von relevanten Belastungs- und/oder Beanspruchungsmarkern ohne zwingend hoch spezialisiertes und geschultes (medizinisches) Fachpersonal mit Zugriff auf ein (Zentral-) Labor, sowie eine schnelle Auswertung dieser Daten und damit potenziell sofortiges (Bio-)Feedback.

Obwohl sich einige ihrer Eigenschaften überschneiden, werden hier „Apps“ als ausführbare Software, die auf Handheld-Geräten wie Smartphones und manchmal Smartwatches ausgeführt wird, definiert. POCT-Geräte werden als Produkte definiert, welche häufig auf minimal invasive Weise eine schnelle biochemische, hämatologische, gerinnungsspezifische oder molekulare Diagnostik am Ort des Geschehens (z. B. auf dem Trainingsgelände) ermöglichen.

Ziel der *Studie 5* war es ein theoretisches Rahmenmodell zu entwickeln, welches Apps, Wearables und POCT-Geräte verwendet und welches erlaubt, relevante Belastungs- und/oder Beanspruchungsmarker zu jeweils relevanten Zeitpunkten im Tages- und/oder Wochenverlauf zu erfassen, um Trainingsprozesse individuell steuern zu können. Das Rahmenmodell inklusive der Technologien und erfassbaren Markern ist gezielt offengehalten, um für möglichst viele Sportarten anwendbar zu sein. Die weitere Anpassung und Ausdifferenzierung des dargelegten Rahmenmodells, die Auswahl der spezifischen Technologien und Marker sowie der Zeitpunkt und die Häufigkeit ihrer Erfassung sind zum Beispiel abhängig von der jeweiligen Sportart, den Präferenzen des Trainerteams und der Athleten.

Tabelle 1: *Belastungsmarker, welche mithilfe von Wearables, Apps und/oder Point-of-Care Testing-Geräten erfasst werden können (abgedruckt mit Erlaubnis von: Sensors (Basel)).*

Type of Parameter	Individual Parameters	Method/Sensor Technology	Additional Comments
Duration and frequency of training sessions	- Time - Number	Sport watches	Sport watches allow automatic storage of data in the "cloud"
Distance covered (in different speed zones)	e.g., - absolute value - relative value - acute:chronic workload ratio	Global Navigation Satellite Systems	- Only useful outdoors - High sampling frequency required
		Local positioning systems	In- and outdoors
Short explosive activities	e.g., - absolute accelerations - relative accelerations	Inertial measurement units	Embedded in a Global Navigation Satellite System receiver unit
Sleep	- Quantity - Circadian rhythm	Actigraphy	Actigraphy should only be used with caution to access sleep quality.
Environmental factors	- Temperature - Altitude - Ultra-violet radiation - Humidity	- Thermometer - Barometer - Hygrometer	

Zusätzlich zu den in *Studie 1* aufgelisteten Markern, die potenziell mit Wearables erfasst werden können, wurden in *Studie 5* Marker identifiziert, welche mit Apps und/oder POCT-Geräten non- oder zumindest minimalinvasiv erfassbar sind. Diese Marker sind in Tabellen 1 und 2 aufgelistet. Der Zusammenhang dieser Marker im Kontext der individualisierten Steuerung von Trainingsprozessen wird in dem veröffentlichten Fachzeitschriftenartikel dargelegt.

Tabelle 2: *Beanspruchungsmarker, welche mithilfe von Wearables, Apps und/oder Point-of-Care-Testing Geräten erfasst werden können (abgedruckt mit Erlaubnis von: Sensors (Basel))*

Type of Parameter	Individual Parameter	Area of Interest
General health	Core, body or skin temperature	Thermoregulation
	White blood cell count	Infections
	High-sensitive C-reactive Protein	Inflammation
	Immunoglobulin A (IglA)	Mucosal immune function
	Reactive Oxygen Species	Oxidative stress
	Haemoglobin	Anaemia and dehydration
	Ferritin	Iron deficiency
Bio-psychological stress	Cortisol	- Protein degradation - Suppression of immune function
	Alpha-amylase	Stress on the sympathetic nervous system
Subjective parameters	Questionnaires and diaries	Various psychological aspects

Parameters of cardiac stress	Cardiac troponin	Myocardial stress
	Fatty acid-binding protein	
	Heart rate during exercise	
	Heart rate variability	Cardiac autonomous nervous system
	Heart rate recovery	Overreaching
Parameters of muscle damage	Aspartate aminotransferase	Breakdown of muscle cell structure Protein catabolism
	Creatine kinase	
	Myoglobin	
	Lactate dehydrogenase	
Parameters of metabolism	Lactate	Endurance performance
	Urea	Elevated protein catabolism
	Uric acid	Enhanced metabolic strain when muscle stores of glycogen are depleted
	Creatinine	Renal functioning
	Testosterone	Non-functional overreaching
	Tissue oxygenation	Intensity of effort
	pH	Acid-base status

Das entwickelte Rahmenmodell (Abbildung 7) zur Individualisierung und situativen Anpassung von Trainingsprozessen zeigt die Kombination aus Wearables, Apps und POCT-Geräten, welche aufgrund ihrer Handhabbarkeit und/oder aufgrund Besonderheiten des jeweils zu erfassenden Markers unterschiedlich häufig und zu unterschiedlichen Tages- oder Wochenzeiten eingesetzt werden können.

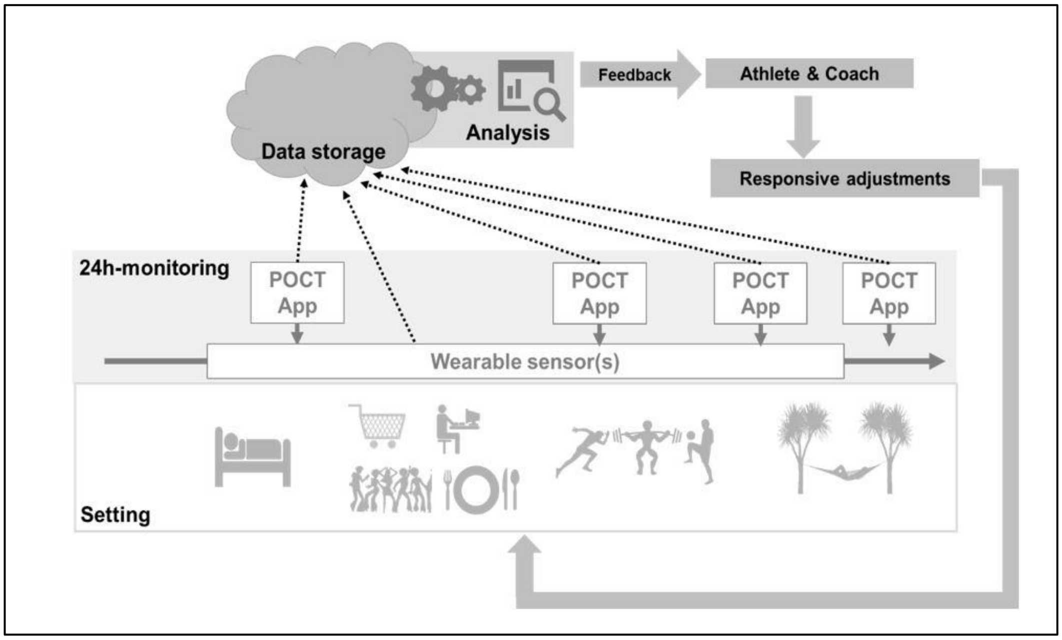

Abbildung 7: *Rahmenmodell zur Kombination von Wearables, Apps und POCT Geräten zur Erfassung verschiedener Belastungs- und Beanspruchungsmarker (abgedruckt mit Erlaubnis von: Sensors (Basel))*

Aufgrund der non-Invasivität der Marker und einem tendenziell hohen Tragekomfort, ihrer Unauffälligkeit sowie der einfachen Handhabung ermöglichen Wearables ein weitgehend kontinuierliches Monitoring verschiedener Marker während des Trainings, der Erholung, während Zeiten normaler körperlicher (In-)Aktivität neben dem Training („Off-Training“) (Sperlich & Holmberg, 2017a) und, sofern von den reglementierenden Organen der jeweiligen Sportart genehmigt, auch während Wettkämpfen (Brud, 2015; IAAF, 2017).

Subjektive Daten, die beispielsweise via Apps erfassbar sind, können punktuell je nach Bedarf und in Abhängigkeit des jeweiligen Markers zum Beispiel einmal pro Tag oder einmal pro Woche erhoben werden. Als Beispiel können hier die Abfrage nach dem Belastungsempfinden anhand der von Gunnar Borg entwickelten „Ratings of Perceived Exertion“-Skala am Ende einer Trainingseinheit (Borg, 1970) oder die „Akute-Erholungs-und-Stress-Skala“ (Nassi et al., 2017) am Ende eines Mikrozyklus dienen.

Da POCT-Geräte häufig Kapillarblut (beispielsweise zur Erfassung von Kreatinkinase) oder Speichel (beispielsweise zur Erfassung von Cortisol oder Testosteron) zur Erfassung von Markern benötigen, können Marker mit diesen Technologien nicht so häufig wie mithilfe von Wearables und/oder Apps erfasst werden.

In *Studie 5* wird hervorgehoben, dass mithilfe von Wearables und/oder Apps Marker während dem Off-Training erfasst werden können. Dies erscheint relevant, da selbst Hochleistungssportler lediglich circa 17% ihrer Wachzeit mit Training und die restlichen 83% im Off-Training verbringen (Fiskerstrand & Seiler, 2004). Zu einer umfassenden Erfassung von Beanspruchungs- und Belastungsmarkern zur individualisierten Steuerung von Trainingsprozessen kann es daher hilfreich sein, Marker während des Off-Trainings zu erfassen. Allerdings ist die derzeitige wissenschaftliche Evidenzlage, welche Marker für welche Sportart und für welche Population zu welchem Zeitpunkt einen Mehrwert zur individualisierten Steuerung von Trainingsprozessen haben, stark limitiert und weitere Forschung in diesem Bereich wird benötigt.

Obwohl es für die in den Tabellen der *Studien 1* und *5* aufgelisteten Belastungs- und Beanspruchungsmarker physiologische und/oder psychologische Zusammenhänge im Hinblick auf die individualisierte Steuerung von Trainingsprozessen gibt, müssen zukünftige Studien dessen Effektivität in der sportartspezifischen Praxis evidenzbasiert belegen. *Studie 4* gibt für den Marker HRV eine erste Tendenz bei Läufern, dass bei richtigem Monitoring sowie Interpretation des Markers gewisse physiologische Adaptationen sowie eine Leistungsverbesserung wahrscheinlich eher erzielt werden können, als ein nicht individualisiert gesteuerter Trainingsprozess. Es muss in zukünftigen Studien gezeigt werden, welcher Marker oder welche Markerkombination für welche Population und Sportart in welcher Phase der Trainings- und/oder der Wettkampfvorbereitung anderen Markern und/oder Markerkombinationen im Hinblick auf die individualisierte Steuerung von Trainingsprozessen zur Steigerung der Leistungsfähigkeit und/oder gewisser physiologischer Adaptionen überlegen sind.

2.6. **Studie 6:** Düking, P, Stammel C, Sperlich B, Sutehall S, Muniz-Pardos B, Lima G, Kilduff L, Keramitsoglou I, Li G, Pigozzi F, Pitsiladis YP. (2018). **Necessary Steps to Accelerate the Integration of Wearable Sensors Into Recreation and Competitive Sports.** *Curr Sports Med Rep*. (6):178-82.

FIMS: INTERNATIONAL PERSPECTIVES

Necessary Steps to Accelerate the Integration of Wearable Sensors Into Recreation and Competitive Sports

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Ziel der *Studie 6* war es, notwendige Faktoren aufzuzeigen, welche verändert werden müssen, wenn Wearables weiter zum Monitoring verschiedener physiologischer und/oder biomechanischer Belastungs- und/oder Beanspruchungsmarker zur individualisierten Steuerung von Trainingsprozessen integriert werden sollen.

1) Evidenzbasierte Grundlage zur Relevanz der Messung eines Markers

Getrieben durch technologische Entwicklungen werden neue Belastungs- und Beanspruchungsmarker in der Praxis erfassbar werden. Beispielsweise befinden sich Wearables, welche Muskelaktivitäten mithilfe drucksensitiver Sensoren und/oder Kräfte in Kreuzbändern bei verschiedenen Bewegungen approximieren im Forschungsstadium (A. Belbasis, F.K. Fuss, & J. Sidhu, 2015a; Belbasis et al., 2015b). Für jeden Marker, der erfasst werden soll, muss eine wissenschaftliche Evidenzbasis gegeben sein, welche die Erfassung des Markers und die individualisierte Steuerung von Trainingsprozessen rechtfertigt. *Studie 4* zeigt, dass mithilfe prospektiver Studien und systematischer Reviews diese wissenschaftliche Evidenzbasis erlangt werden kann. Jedoch kann der Nachweis der wissenschaftlichen Evidenzbasis ein schwieriger und langwieriger Prozess sein, insbesondere wenn das Ziel der individualisierten Steuerung von Trainingsprozessen eine Verringerung der Verletzungswahrscheinlichkeit ist. Dies kann am Beispiel von Positionsdaten (aus welchen Marker wie beispielsweise die zurückgelegte Distanz in verschiedenen Geschwindigkeitszonen errechnet wird), welche heutzutage bereits vermehrt in verschiedenen Sportarten erfasst und insbesondere zur Verringerung der Wahrscheinlichkeit von Verletzungen genutzt werden, erläutert werden (Colby, Dawson, Heasman, Rogalski, & Gabbett, 2014; Hulin, Gabbett, Lawson, Caputi, & Sampson, 2016). Es konnte in retroperspektivischen Studien nachgewiesen werden, dass es Zusammenhänge zwischen der relativen Verletzungswahrscheinlichkeit und der Belastung, ermittelt durch GPS-Sensoren, gibt (Gabbett, Hulin, Blanch, & Whiteley, 2016; Hulin, Gabbett, Caputi, Lawson, & Sampson, 2016; Hulin, Gabbett, Lawson, et al., 2016). Eine retroperspektivisch errechnete Korrelation zwischen einem Marker (im gegebenen Beispiel der zurückgelegten Distanz in verschiedenen Geschwindigkeitszonen) und einem Resultat (z. B. Verringerung der Verletzungswahrscheinlichkeit) belegt jedoch nicht die Vorhersagbarkeit des Resultats durch den Marker (Bahr, 2016; Fanchini et al., 2018). Eine Studie zeigt, obwohl eine signifikante Korrelation zwischen einem Marker und einem Resultat besteht, die Vorhersagbarkeit des Resultats basierend auf dem Marker für das Individuum nicht gegeben sein muss (Fanchini et al., 2018). Die Anwendung von Positionsdaten zur individualisierten Steuerung von Trainingsprozessen mit dem Ziel der Verringerung von Verletzungswahrscheinlichkeiten muss daher hinterfragt werden. Derzeit ist (nach bestem Wissensstand) keine prospektive Studie bekannt, welche die Vorhersagekraft von positionsbezogenen Daten auf Verletzungen untersucht.

2) Unabhängige Qualitätskontrollen

Eine unabhängige Qualitätskontrolle (wie in den *Studien 2* und *3*), welche mindestens die Reliabilität und Validität der von Wearables bereitgestellten Daten und Markern evaluiert, ist unerlässlich, wenn diese zur individualisierten Steuerung von Trainingsprozessen genutzt werden sollen (Düking, Fuss, Holmberg, & Sperlich, 2018; Sperlich & Holmberg, 2017b). Dieses Thema wurde in den *Studien 2* und *3* ausführlich erläutert. Daher bedarf es hier keiner weiteren Ausführungen.

3) Gestaltung der Informationsdarstellung

Für verschiedene Sportarten sowie Sportler muss die Art der Informationsdarstellung der Marker ausdifferenziert und angepasst werden. Hier ist eine Zusammenarbeit mit Athleten und Trainern erforderlich. Die Informationen zur individualisierten Steuerung von Trainingsprozessen sollten einfach und schnell verständlich sowie idealerweise in ästhetisch ansprechender Form präsentiert werden (Buchheit, 2017).

Wenn Marker während des Sports direkt an den Athleten weitergegeben werden (z. B. visuell, auditiv, taktil), darf dieser nicht bei der Ausführung der Sportart gestört werden (Buchheit, 2017). Dies erscheint von besonderer Relevanz, wenn die geringste Ablenkung die Leistung und/oder Gesundheit der Athleten beeinträchtigen kann. Als Beispiel kann visuelles Feedback bei Sportarten mit hohen Geschwindigkeiten wie alpinem Skifahren dienen. Jegliche subjektiv wahrgenommene visuelle Störung durch Feedback von Daten ist zu vermeiden. Es gibt derzeit wenige Studien, welche verschiedenste Formen von Feedback in verschiedenen Sportarten und Athletenpopulationen vergleichen. Erforderlich sind zukünftige Studien, die die nützlichste und geeignetste Form des Feedbacks für verschiedene sportliche Aufgaben und Disziplinen finden (Buchheit, 2017).

3. Diskussion

Übergeordnetes Ziel der vorliegenden kumulativen Dissertation war es, den Einsatz von Wearables zum Monitoring von Belastungs- und/oder Beanspruchungsmarkern zur individualisierten Steuerung von Trainingsprozessen aus physiologisch-trainingswissenschaftlicher Perspektive zu untersuchen. Die durchgeführten *Studien 1-6* zeigen,

1) dass einige, aber nicht alle relevanten Belastungs- und Beanspruchungsmarker mit derzeit kommerziell erhältlichen reliable und valide mit ausgewählten Wearables erfasst werden können (*Studie 1, 3*),
2) dass viele Marker, die von Wearables erhoben werden, nicht auf Reliabilität und/oder Validität hin untersucht worden sind und/oder dass sich die Reliabilität und/oder Validität zwischen Wearables und zwischen verschiedenen sportlichen Aktivitäten unterscheidet (*Studie 1, 2, 3*),
3) dass die Apple Watch Series 4, gefolgt von der Polar Vantage V, die derzeit beste Validität zur Erfassung der Herzfrequenz bei Athleten während verschiedenen Laufintensitäten aufweist (*Studie 3*),
4) dass bei Läufern ein individualisiert gesteuerter Trainingsprozess (basierend auf Daten des autonomen Nervensystems erfasst durch Wearables) zu größeren Leistungsverbesserungen und ausgewählten submaximalen physiologischen Adaptionen führt, als ein nicht individualisiert gesteuerter Trainingsprozess (*Studie 4*),
5) dass ein theoretisches Rahmenmodell, welches verschiedene Technologien (Wearables, Smartphone-Applikationen und Point-of-Care-Testing-Geräte) zur weiteren Ausdifferenzierung eines individualisiert gesteuerten Trainingsprozesses vereint (*Studie 5*),

6) einige Faktoren auf, welche die weitere Integration von Wearables zur individualisierten Steuerung von Trainingsprozessen fördern (*Studie 2, 4, 5, 6*).

Neben der physiologisch-trainingswissenschaftlichen Perspektive muss der Einsatz von Wearables zum Monitoring von Belastungs- und/oder Beanspruchungsmarkern zur individualisierten Steuerung von Trainingsprozessen aus der Perspektive weiterer wissenschaftlicher Disziplinen (z.B. Psychologie, Pädagogik, Soziologie etc.) untersucht werden.

Im Folgenden werden anhand des in Studie 5 dargestellten Rahmenmodells verschiedene offene Fragestellungen angesprochen (Abbildung 10). Diese Fragestellungen sind nicht klar voneinander trennbar und müssen mithilfe verschiedener wissenschaftlicher Fachdisziplinen beantwortet werden. Die hier folgenden Ausführungen sind nicht als abschließend, sondern als Start für eine Diskussion zu sehen, um den Einsatz von Wearables zur Steuerung von Trainingsprozessen kritisch zu hinterfragen, zu evaluieren und zielgerichtet sowie für den Anwender gewinnbringend weiterzuentwickeln.

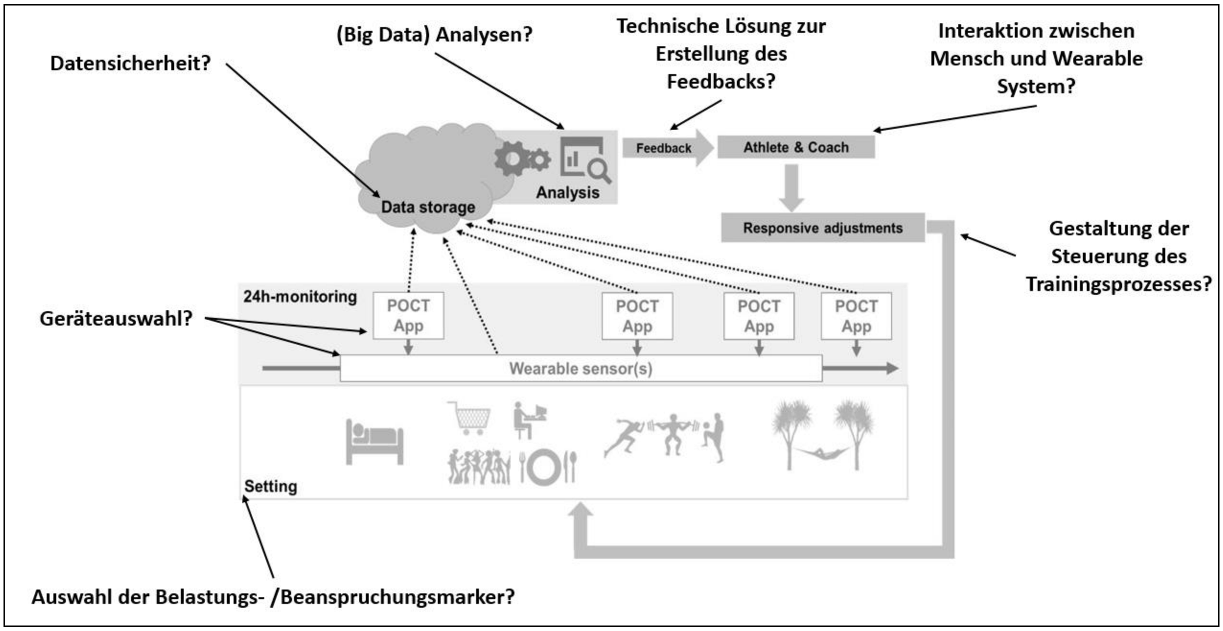

Abbildung 8: *Offene Fragen zum Einsatz von Wearables zur individualisierten Steuerung von Trainingsprozessen*

1) Auswahl der Belastungs-/Beanspruchungsmarker

Es bleibt die Frage (wie bereits in *Studie 5* und *6* erwähnt), welcher Marker oder welche Markerkombination für welche Population in welcher Sportart in welcher Phase der Trainings- und/oder der Wettkampfvorbereitung anderen Markern und/oder Markerkombinationen im Hinblick auf die individualisierte Steuerung von Trainingsprozessen zur Steigerung der Leistungsfähigkeit und/oder gewisser physiologischer Adaptionen überlegen ist/sind. Das Erfassen eines Markers erfüllt keinen Selbstzweck (Baker, 2020), es ist vielmehr die kontextabhängige sowie evidenzbasierte Interpretation der Marker zur Steuerung von Trainingsprozessen entscheidend. Für jeden Marker, der erfasst werden soll, muss eine wissenschaftliche Evidenzbasis gegeben sein, welche die Erfassung des Markers und die individualisierte Steuerung von Trainingsprozessen rechtfertigt.

2) Geräteauswahl

Es bleibt die Frage, welches Wearable zum Monitoring von Belastungs- und Beanspruchungsmarkern zur individualisierten Steuerung von Trainingsprozessen verwendet wird. Aufgrund des technologischen Fortschritts und der sich stetig wandelnden verfügbaren Wearables wird hier eine ständige Evaluation nötig sein. Wie in *Studien 2, 3* und *6* dargelegt, müssen Reliabilität und Validität der zur Verfügung gestellten Marker gewährleistet sein. Eine Standardisierung sowie unabhängige Instanz, welche die Wearables hierauf überprüft und gegebenenfalls zertifiziert, erscheint sinnvoll. Weiter sollten für die Sportpraxis technologische Aspekte wie Akkulaufzeit, Dauer der Ladezyklen, Speicherkapazität, Geschwindigkeit der Datenanalyse sowie die generelle Handhabung der Geräte zur Steigerung der dauerhaften Anwendbarkeit berücksichtigt werden (Düking, Achtzehn, et al., 2018; Hosseinpour & Terlutter, 2019; Loncar-Turukalo, Zdravevski, Machado da Silva, Chouvarda, & Trajkovik, 2019).

3) Datensicherheit

Weiterhin bestehen Fragen zur Datensicherheit. Der Schutz der persönlichen, mithilfe von Wearables erhobenen Daten ist entscheidend für deren Nutzung (Austen, 2015; Loncar-Turukalo et al., 2019; Segura Anaya, Alsadoon, Costadopoulos, & Prasad, 2018). Auch wenn es technologisch möglich ist, die Daten von Wearables zu verschlüsseln bleibt fraglich, ob gerade einfache, kostengünstige sowie nicht medizinische Wearables ein ausreichendes Maß an Datensicherheit liefern (Austen, 2015). Da viele Wearables die zum Monitoring von Athleten verwendet werden keine medizintechnischen Produkte sind, unterliegen diese auch nicht den dort geltenden Datenschutzrichtlinien (z.B. dem „Health Insurance Portability and Accountability Act“ oder dem „FDA Safety and Innovation Act“) (Lobelo et al., 2016). Da es derzeit für Wearables, welche für Sportler vermarktet werden, keine geltenden Vorgaben zur Datensicherheit gibt, muss im Einzelfall geprüft werden, ob ein ausreichender Datenschutz besteht.

4) (Big Data-) Analysen

Wearables ermöglichen sowohl im Längs-, als auch im Querschnitt die Erhebung von großen Datenmengen. Dadurch wird es möglich Algorithmen aus dem Bereich der „Big Data“-Analysen, wie künstliche Intelligenzen (KI), zu entwickeln und anzuwenden. Obwohl keine einheitliche Definition von künstlicher Intelligenz vorhanden ist, beschreibt KI die Verwendung von Algorithmen mit dem Ziel eine Intelligenz zu schaffen, die das menschliche Denken nachbildet (Nilsson, 2009). Es bleibt die Frage, ob in Zukunft „Big Data“-Analysen einen Mehrwert zur individualisierten Steuerung von Trainingsprozessen liefern können. KI hält mit unterschiedlichem Erfolg Einzug in verschiedene wirtschaftliche sowie wissenschaftliche Bereiche (z. B. Verbesserung der Radiologie im Bereich der Bild- und Mustererkennung (Hosny, Parmar, Quackenbush, Schwartz, & Aerts, 2018; Schaffter et al., 2020). Gerade im Bereich der personalisierten Medizin, insbesondere unter ethischen Gesichtspunkten, wird der Einsatz von Big Data und KI allerdings kontrovers diskutiert (Emanuel & Wachter, 2019; Yu, Beam, & Kohane, 2018)).

Ob und inwiefern KI im sportlichen Kontext und insbesondere zur individualisierten Steuerung von Trainingsprozessen einen Mehrwert liefert, ist derzeit noch weitestgehend unerforscht. Dies wird zum Beispiel dadurch belegt, dass im Jahr 2019 das Bundesinstitut für Sportwissenschaft eine Ausschreibung mit dem Ziel einen „Überblick über derzeitige nationale und internationale Einsatzgebiete und den Nutzen von KI und insbesondere Machine Learning im Spitzensport aufzuzeigen“ ausgeschrieben hat (Sportwissenschaft, 2019). Die zukünftige Forschung muss den Einsatz und Mehrwert von KI im Sport und zur Steuerung von Trainingsprozessen erforschen.

5) Technische Lösung zur Erstellung des Feedbacks

Es bleibt die Frage, wie aus technischer Sicht ein (Bio-)Feedback zur optimalen individualisierten Steuerung von Trainingsprozessen gestaltet werden muss. Es ist bekannt, dass verschiedene Arten des (Bio-)Feedbacks in verschiedenen Populationen unterschiedlich effektiv sind (Baker, 2020; Hosseinpour & Terlutter, 2019). Beispielsweise ist im Bereich der Erhöhung der körperlichen Alltagsaktivität bekannt, dass die Implementierung der Zielsetzung (bspw. Anzahl an Schritten pro Tag) oder das Teilen von Erfolgen auf sozialen Plattformen erfolgversprechender als beispielsweise das Anzeigen von Erfolgen in Form von Trophäen ist (Hosseinpour & Terlutter, 2019). Gleichzeitig ist auch bekannt, dass ein (Bio-)Feedback von Markern, erhoben durch Wearables, auch negative Konsequenzen (z.B. hervorrufen von Angstzuständen, Demotivation) haben kann (Baker, 2020; Halson, Peake, & Sullivan, 2016).

Derzeit ist nicht geklärt, welche Art des Feedbacks (z. B. visuell, auditiv, vibrotaktil) in welcher Sportart und welcher Athletenpopulation am Vielversprechendsten zur individualisierten Steuerung von Trainingsprozessen ist. Aus praktischer Sicht sollte das (Bio-)Feedback einfach verständlich und auf die wesentlichen Informationen reduziert sein sowie im Idealfall Handlungsempfehlungen enthalten (Baker, 2020; Buchheit, 2017). Das jeweilige (Bio-)Feedback sollte in Zusammenarbeit mit Trainern und Athleten der entsprechenden Sportart sowie mit Hilfe von Experten im Bereich des technologischen (Bio-)Feedbacks evidenzbasiert entwickelt werden (Baker, 2020).

6) Interaktion zwischen Mensch und Wearable-System

Es stellt sich die Frage, wie Trainer und Athleten mit Wearables zum Monitoring und zur Steuerung von Trainingsprozessen interagieren, selbst wenn aus technologischer Sicht die vorher genannten

Punkte 1 bis 4 (Auswahl der Marker und Geräte, Datensicherheit, Analyseverfahren, (Bio-)Feedback) aus physiologischer sowie technologischer Sicht für einzelne Sportarten gelöst sind. Diese Frage kann hier aufgrund der Interdisziplinarität der Fragestellung, der Besonderheiten der einzelnen Sportarten sowie persönlichen Präferenzen der Trainer und Athleten nicht umfänglich beantwortet werden. Aus der medizinischen Anwendung und Forschung lässt sich aber ein Ansatz entnehmen, der übertragen auf den Sport zur Anwendung von Wearables zum Monitoring von Belastungs- und/oder Beanspruchungsmarkern Anwendung finden könnte.

Auch in der Medizin sind Tendenzen zu erkennen, dass Systeme welche (teilweise mithilfe von Wearables erhobenen) Daten mithilfe verschiedener Algorithmen analysieren und über ein (Bio-) Feedback rückmelden, einen großen Enthusiasmus auslösen, da sie in bestimmten Aufgaben vergleichbare Leistungen erbringen wie medizinisches Fachpersonal (Abramoff, Lavin, Birch, Shah, & Folk, 2018). Jedoch stellen sich auch in der Medizin neben technologischen Fragen wie zum Beispiel des Datenschutzes oder der genauen Algorithmen die Frage, wie medizinisches Fachpersonal und der Patient mit diesen Systemen interagieren.

Ein möglicher Lösungsansatz in der Medizin zur Verbesserung der Patientenversorgung ist die graduelle Einführung datengestützter Systeme (Verghese, Shah, & Harrington, 2018). Abbildung 9 zeigt diese graduelle Einführung schematisch.

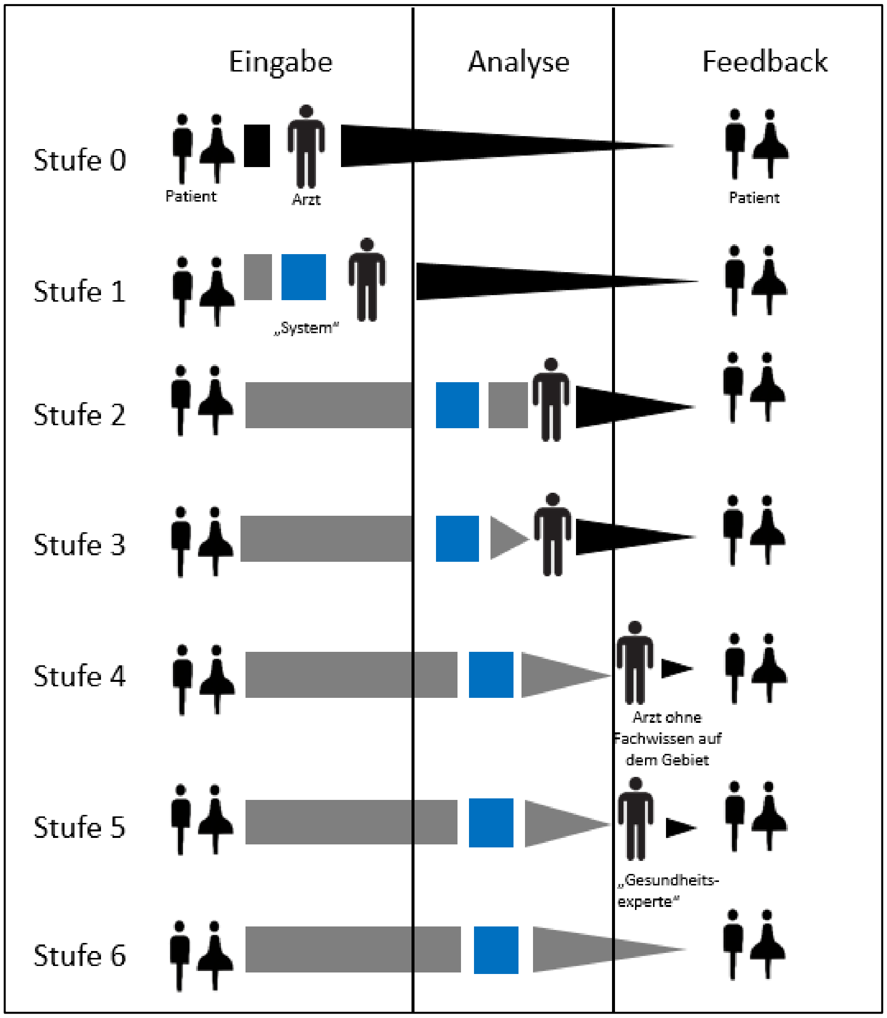

Abbildung 9: *Modell zur graduellen Interaktion zwischen Mensch und Wearable-System. Modifiziert nach (Ema, Nagakura, & Fujita, 2020). Hellgrau ist die Informationsaufnahme und -analyse sowie das Feedback des Systems, schwarz die des Arztes dargestellt.*

Die einzelnen Stufen werden im Folgenden näher erläutert (Ema et al., 2020).

Stufe 1: Das System unterstützt die Erfassung und Eingabe von Informationen, die zur Unterstützung des Facharztes beitragen.

Stufe 2: Die Systeme unterstützen Fachärzte bei der Entscheidungsfindung.

Stufe 3: Die Fachärzte führen medizinische Aktivitäten basierend auf den Empfehlungen des Systems durch.

Stufe 4: Ärzte, welche keine ausgereiften Kenntnisse auf dem jeweiligen Fachgebiet haben, führen Aktivitäten auf der Grundlage der Empfehlungen des Systems durch.

Stufe 5: Das System bietet medizinische Versorgung und präsentiert „Gesundheitsexperten“ (welches keine Ärzte sind) Diagnoseergebnisse und Handlungsempfehlungen.

Stufe 6: Das System bietet dem Endkonsumenten Diagnoseergebnisse und Handlungsempfehlungen.

Kritische Voraussetzungen in der Medizin zur Verwirklichung der graduellen Einführung der datengestützten Systeme zur Verbesserung der Patientenversorgung ist die Überprüfung der Reliabilität, Validität sowie Effektivität zwischen und während den einzelnen Stufen in verschiedenen Populationen und Settings. Diese Überprüfungen gibt es derzeit für Wearables zur Steuerung von Trainingsprozessen im Sport nicht. Aus diesem Grund finden sich Wearables auf dem Markt, die entsprechend der oben aufgelisteten Stufen suggerieren, bereits auf der hier angegebenen Stufe 6 zu sein, ohne dass hierfür wissenschaftliche Evidenz vorliegt. Dies muss äußerst kritisch betrachtet werden. Eine Reglementierung und unabhängige Kontrollinstanz während und zwischen den einzelnen Stufen wird dringend benötigt, wenn im Sport datengestützte Systeme zur Steuerung von Trainingsprozessen graduell eingeführt werden sollen.

7) Gestaltung der Steuerung des Trainingsprozesses

Es bleibt die Frage, mithilfe welcher Intervention der Trainingsprozess optimal auf Grundlage von Daten abgeändert und damit situativ gesteuert wird.

Studie 4 zeigt, wenn auf Grundlage des Markers HRV eine Reduktion der intensiven Trainingseinheiten stattfindet, größere Leistungsverbesserungen als bei einem nicht situativ angepassten Trainingsvorgaben zu erwarten sind. Fraglich bleibt jedoch, ob die Reduktion der intensiven Trainingseinheiten die optimale Form der Abänderung des Trainingsprozesses ist. Es liegen derzeit keine Studien vor, die beispielsweise anstelle der Reduktion der Trainingsintensität verschiedene Erholungsstrategien (beispielsweise Kaltwasserimmersionen oder Massagen (Wiewelhove et al., 2018)) verwenden. Die zukünftige Forschung sollte die Effektivität verschiedener Abänderungen des Trainingsprozesses als Reaktion auf Veränderungen der HRV untersuchen.

Wird ein anderer Marker als Grundlage zur Steuerung des Trainingsprozesses verwendet, müssen auch hier verschiedene Änderungen des Trainings miteinander im Hinblick auf ihre Effektivität verglichen werden.

4. Zusammenfassung

Es kann festgehalten werden, dass viele, aber nicht alle relevanten Belastungs- und/oder Beanspruchungsmarker reliabel und valide bei korrekter Auswahl und Anwendung von ausgewählten Wearables erfasst werden können, welche bei kontextabhängiger korrekter Interpretation zur individualisierten Steuerung von Trainingsprozessen mit dem Ziel der Leistungsoptimierung genutzt werden können. Dennoch besteht aus trainingswissenschaftlicher Perspektive weiterer Forschungsbedarf, insbesondere im Hinblick auf die für die jeweilige Sportart und Population ideale Marker- und Geräteauswahl, sowie auf die Evidenz der optimalen Art der Abänderung des Trainingsprozesses.

Es muss ein System entwickelt werden, das verschiedene Marker (erhoben mithilfe von Wearables und weiteren Technologien) mit ausreichendem Datenschutz erfasst und vereint sowie das gegebenenfalls „Big Data"-Analysen (welche Ihren Mehrwert im gegebenen Kontext noch Nachweisen müssen) ermöglicht. Bei der graduellen Einführung von Wearables müssen verschiedene Kontrollinstanzen eingeführt werden. Weiter müssen Trainer und Athleten im Umgang mit Daten und deren kontextabhängiger Interpretation geschult werden, damit datengestützte Entscheidungen zur Steuerung von Trainingsprozessen getroffen werden können.

5. Literaturverzeichnis

Abramoff, M. D., Lavin, P. T., Birch, M., Shah, N., & Folk, J. C. (2018). Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices. *NPJ Digit Med, 1*, 39. doi:10.1038/s41746-018-0040-6

Austen, K. (2015). What could derail the wearables revolution? *Nature, 525*(7567), 22-24. doi:10.1038/525022a

Bacon, A. P., Carter, R. E., Ogle, E. A., & Joyner, M. J. (2013). VO2max trainability and high intensity interval training in humans: a meta-analysis. *PLoS One, 8*(9), e73182. doi:10.1371/journal.pone.0073182

Bahr, R. (2016). Why screening tests to predict injury do not work-and probably never will...: a critical review. *Br J Sports Med, 50*(13), 776-780. doi:10.1136/bjsports-2016-096256

Baker, D. A. (2020). Four Ironies of Self-quantification: Wearable Technologies and the Quantified Self. *Sci Eng Ethics*, 1-22. doi: 10.1007/s11948-020-00181-w

Belbasis, A., & Fuss, F. K. (2018). Muscle Performance Investigated With a Novel Smart Compression Garment Based on Pressure Sensor Force Myography and Its Validation Against EMG. *Front Physiol, 9*, 408. doi:10.3389/fphys.2018.00408

Belbasis, A., Fuss, F. K., & Sidhu, J. (2015a). *Estimation of cruciate ligament forces via smart compression garments*. Paper presented at the 7th Asia-Pacific Congress on Sports Technology, Barcelona.

Belbasis, A., Fuss, F. K., & Sidhu, J. (2015b). *Muscle Activity Analysis with a Smart Compression Garment* Paper presented at the 7th Asia-Pacific Congress on Sports Technology.

Borg, G. (1970). Perceived exertion as an indicator of somatic stress. *Scand J Rehabil Med, 2*(2), 92-98.

Bouchard, C., An, P., Rice, T., Skinner, J. S., Wilmore, J. H., Gagnon, J., . . . Rao, D. C. (1999). Familial aggregation of VO(2max) response to exercise training: results from the HERITAGE Family Study. *J Appl Physiol (1985), 87*(3), 1003-1008. doi:10.1152/jappl.1999.87.3.1003

Boudreaux, B. D., Hebert, E. P., Hollander, D. B., Williams, B. M., Cormier, C. L., Naquin, M. R., . . . Kraemer, R. R. (2018). Validity of Wearable Activity Monitors during Cycling and Resistance Exercise. *Med Sci Sports Exerc, 50*(3), 624-633. doi:10.1249/MSS.0000000000001471

Brud, L. (2015). Amendments to the Laws of the Game – 2015/2016 and information on the completed reform of The International Football Association Board. Retrieved from http://resources.fifa.com/mm/document/affederation/ifab/02/60/91/38/circular_log_amendments_2015_v1.0_en_neutral.pdf

Buchheit, M. (2017). Want to see my report, coach. *Sport Science Reporting in the Real World. Aspetar Sports Med. J, 6*, 36-42.

Colby, M. J., Dawson, B., Heasman, J., Rogalski, B., & Gabbett, T. J. (2014). Accelerometer and GPS-derived running loads and injury risk in elite Australian footballers. *J Strength Cond Res, 28*(8), 2244-2252. doi:10.1519/JSC.0000000000000362

Dooley, E. E., Golaszewski, N. M., & Bartholomew, J. B. (2017). Estimating Accuracy at Exercise Intensities: A Comparative Study of Self-Monitoring Heart Rate and Physical Activity Wearable Devices. *JMIR Mhealth Uhealth, 5*(3), e34. doi:10.2196/mhealth.7043

Duden. (2020). Wearable. *Duden.* Retrieved from https://www.duden.de/rechtschreibung/Wearable

Düking, P., Achtzehn, S., Holmberg, H. C., & Sperlich, B. (2018). Integrated Framework of Load Monitoring by a Combination of Smartphone Applications, Wearables and Point-of-Care Testing Provides Feedback that Allows Individual Responsive Adjustments to Activities of Daily Living. *Sensors (Basel), 18*(5). doi:10.3390/s18051632

Düking, P., Fuss, F. K., Holmberg, H. C., & Sperlich, B. (2018). Recommendations for Assessment of the Reliability, Sensitivity, and Validity of Data Provided by Wearable Sensors Designed for Monitoring Physical Activity. *JMIR Mhealth Uhealth, 6*(4), e102. doi:10.2196/mhealth.9341

Düking, P., Holmberg, H. C., & Sperlich, B. (2017). Instant Biofeedback Provided by Wearable Sensor Technology Can Help to Optimize Exercise and Prevent Injury and Overuse. *Front Physiol, 8*, 167. doi:10.3389/fphys.2017.00167

Düking, P., Hotho, A., Holmberg, H. C., Fuss, F. K., & Sperlich, B. (2016). Comparison of Non-Invasive Individual Monitoring of the Training and Health of Athletes with Commercially Available Wearable Technologies. *Front Physiol, 7*, 71. doi:10.3389/fphys.2016.00071

Ema, A., Nagakura, K., & Fujita, T. (2020). *Proposal for Type Classification for Building Trust in Medical Artificial Intelligence Systems.* Paper presented at the Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society.

Emanuel, E. J., & Wachter, R. M. (2019). Artificial Intelligence in Health Care: Will the Value Match the Hype? *JAMA, 321*(23), 2281-2282. doi:10.1001/jama.2019.4914

Fanchini, M., Rampinini, E., Riggio, M., Coutts, A. J., Pecci, C., & McCall, A. (2018). Despite association, the acute: chronic work load ratio does not predict non-contact injury in elite footballers. *Science and Medicine in Football*, 1-7. doi: 10.1080/24733938.2018.1429014

Fiskerstrand, A., & Seiler, K. S. (2004). Training and performance characteristics among Norwegian international rowers 1970-2001. *Scand J Med Sci Sports, 14*(5), 303-310. doi:10.1046/j.1600-0838.2003.370.x

Fry, R. W., Morton, A. R., & Keast, D. (1991). Overtraining in athletes. An update. *Sports Med, 12*(1), 32-65. doi:10.2165/00007256-199112010-00004

Gabbett, T. J., Hulin, B. T., Blanch, P., & Whiteley, R. (2016). High training workloads alone do not cause sports injuries: how you get there is the real issue. *Br J Sports Med, 50*(8), 444-445. doi:10.1136/bjsports-2015-095567

Giles, D., Draper, N., & Neil, W. (2016). Validity of the Polar V800 heart rate monitor to measure RR intervals at rest. *Eur J Appl Physiol, 116*(3), 563-571. doi:10.1007/s00421-015-3303-9

Halson, S. L. (2014). Monitoring training load to understand fatigue in athletes. *Sports Med, 44 Suppl 2*, S139-147. doi:10.1007/s40279-014-0253-z

Halson, S. L., Peake, J. M., & Sullivan, J. P. (2016). Wearable Technology for Athletes: Information Overload and Pseudoscience? *Int J Sports Physiol Perform, 11*(6), 705-706. doi:10.1123/IJSPP.2016-0486

Hohmann, A., & Lames, M. (2002). Der propositionale Gehalt der Trainingsprinzipien und ihr Beitrag zur modernen Konzepten der Trainingssteuerung. *Trainingsprinzipien. Fundament der Trainingswissenschaft*, 29-42.

Hohmann, A., Lames, M., & Letzelter, M. (2002). Einführung in die Trainingswissenschaft.

Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. (2018). Artificial intelligence in radiology. *Nat Rev Cancer, 18*(8), 500-510. doi:10.1038/s41568-018-0016-5

Hosseinpour, M., & Terlutter, R. (2019). Your Personal Motivator is with You: A Systematic Review of Mobile Phone Applications Aiming at Increasing Physical Activity. *Sports Med, 49*(9), 1425-1447. doi:10.1007/s40279-019-01128-3

Hottenrott, K., & Neumann, G. (2010). *Trainingswissenschaft. Ein Lehrbuch in 14 Lektionen*: Meyer & Meyer Verlag.

Hulin, B. T., Gabbett, T. J., Caputi, P., Lawson, D. W., & Sampson, J. A. (2016). Low chronic workload and the acute:chronic workload ratio are more predictive of injury than between-match recovery time: a two-season prospective cohort study in elite rugby league players. *Br J Sports Med*. doi:10.1136/bjsports-2015-095364

Hulin, B. T., Gabbett, T. J., Lawson, D. W., Caputi, P., & Sampson, J. A. (2016). The acute:chronic workload ratio predicts injury: high chronic workload may decrease injury risk in elite rugby league players. *Br J Sports Med, 50*(4), 231-236. doi:10.1136/bjsports-2015-094817

IAAF. (2017). IAAF Competition Rules 2018 - 2019 Retrieved from https://www.iaaf.org/about-iaaf/documents/rules-regulations

Javaloyes, A., Sarabia, J. M., Lamberts, R. P., & Moya-Ramon, M. (2018). Training Prescription Guided by Heart Rate Variability in Cycling. Int J Sports Physiol Perform, 1-28. doi:10.1123/ijspp.2018-0122

Javaloyes, A., Sarabia, J. M., Lamberts, R. P., Plews, D., & Moya-Ramon, M. (2019). Training Prescription Guided by Heart Rate Variability Vs. Block Periodization in Well-Trained Cyclists. J Strength Cond Res. doi:10.1519/JSC.0000000000003337

Johnstone, J. A., Ford, P. A., Hughes, G., Watson, T., & Garrett, A. T. (2012a). Bioharness(TM) multivariable monitoring device: part. I: validity. *J Sports Sci Med, 11*(3), 400-408.

Johnstone, J. A., Ford, P. A., Hughes, G., Watson, T., & Garrett, A. T. (2012b). Bioharness(TM) Multivariable Monitoring Device: Part. II: Reliability. *J Sports Sci Med, 11*(3), 409-417.

Joyner, M. J., & Lundby, C. (2018). Concepts About V O2max and Trainability Are Context Dependent. *Exerc Sport Sci Rev, 46*(3), 138-143. doi:10.1249/JES.0000000000000150

Kiviniemi, A. M., Hautala, A. J., Kinnunen, H., Nissila, J., Virtanen, P., Karjalainen, J., & Tulppo, M. P. (2010). Daily exercise prescription on the basis of HR variability among men and women. *Med Sci Sports Exerc, 42*(7), 1355-1363. doi: 10.1249/MSS.0b013e3181cd5f39

Kiviniemi, A. M., Hautala, A. J., Kinnunen, H., & Tulppo, M. P. (2007). Endurance training guided individually by daily heart rate variability measurements. *Eur J Appl Physiol, 101*(6), 743-751. doi:10.1007/s00421-007-0552-2

Lobelo, F., Kelli, H. M., Tejedor, S. C., Pratt, M., McConnell, M. V., Martin, S. S., & Welk, G. J. (2016). The Wild Wild West: A Framework to Integrate mHealth Software Applications and Wearables to Support Physical Activity Assessment, Counseling and Interventions for Cardiovascular Disease Risk Reduction. *Prog Cardiovasc Dis, 58*(6), 584-594. doi:10.1016/j.pcad.2016.02.007

Loncar-Turukalo, T., Zdravevski, E., Machado da Silva, J., Chouvarda, I., & Trajkovik, V. (2019). Literature on Wearable Technology for Connected Health: Scoping Review of Research Trends, Advances, and Barriers. *J Med Internet Res, 21*(9), e14017. doi:10.2196/14017

Martinmaki, K., & Rusko, H. (2008). Time-frequency analysis of heart rate variability during immediate recovery from low and high intensity exercise. *Eur J Appl Physiol, 102*(3), 353-360. doi:10.1007/s00421-007-0594-5

Montero, D., & Lundby, C. (2017). Refuting the myth of non-response to exercise training: 'non-responders' do respond to higher dose of training. *J Physiol, 595*(11), 3377-3387. doi:10.1113/JP273480

Moore, G. (1965). Cramming more components onto integrated circuits. *Electronics, 38*(8).

Nassi, A., Ferrauti, A., Meyer, T., Pfeiffer, M., & Kellmann, M. (2017). Development of two short measures for recovery and stress in sport. *Eur J Sport Sci, 17*(7), 894-903. doi:10.1080/17461391.2017.1318180

Nilsson, N. J. (2009). *The quest for artificial intelligence*: Cambridge University Press.

Nuuttila, O. P., Nikander, A., Polomoshnov, D., Laukkanen, J. A., & Hakkinen, K. (2017). Effects of HRV-Guided vs. Predetermined Block Training on Performance, HRV and Serum Hormones. *Int J Sports Med, 38*(12), 909-920. doi:10.1055/s-0043-115122

Plews, D. J., Laursen, P. B., Stanley, J., Kilding, A. E., & Buchheit, M. (2013). Training adaptation and heart rate variability in elite endurance athletes: opening the door to effective monitoring. *Sports Med, 43*(9), 773-781. doi:10.1007/s40279-013-0071-8

Rankinen, T., Fuku, N., Wolfarth, B., Wang, G., Sarzynski, M. A., Alexeev, D. G., . . . Bouchard, C. (2016). No Evidence of a Common DNA Variant Profile Specific to World Class Endurance Athletes. *PLoS One, 11*(1), e0147330. doi:10.1371/journal.pone.0147330

Schaffter, T., Buist, D. S. M., Lee, C. I., Nikulin, Y., Ribli, D., Guan, Y., . . . Jung, H. (2020). Evaluation of Combined Artificial Intelligence and Radiologist Assessment to Interpret Screening Mammograms. *JAMA Netw Open, 3*(3), e200265. doi:10.1001/jamanetworkopen.2020.0265

Schwellnus, M., Soligard, T., Alonso, J. M., Bahr, R., Clarsen, B., Dijkstra, H. P., . . . Engebretsen, L. (2016). How much is too much? (Part 2) International Olympic Committee consensus statement on load in sport and risk of illness. *Br J Sports Med, 50*(17), 1043-1052. doi:10.1136/bjsports-2016-096572

Segura Anaya, L. H., Alsadoon, A., Costadopoulos, N., & Prasad, P. W. C. (2018). Ethical Implications of User Perceptions of Wearable Devices. *Sci Eng Ethics, 24*(1), 1-28. doi:10.1007/s11948-017-9872-8

Seiler, K. S., & Kjerland, G. O. (2006). Quantifying training intensity distribution in elite endurance athletes: is there evidence for an "optimal" distribution? *Scand J Med Sci Sports, 16*(1), 49-56. doi:10.1111/j.1600-0838.2004.00418.x

Singh, N., Moneghetti, K. J., Christle, J. W., Hadley, D., Plews, D., & Froelicher, V. (2018). Heart Rate Variability: An Old Metric with New Meaning in the Era of using mHealth Technologies for Health and Exercise Training Guidance. Part One: Physiology and Methods. *Arrhythm Electrophysiol Rev, 7*(3), 193-198. doi:10.15420/aer.2018.27.2

Soligard, T., Schwellnus, M., Alonso, J. M., Bahr, R., Clarsen, B., Dijkstra, H. P., . . . Engebretsen, L. (2016). How much is too much? (Part 1) International Olympic Committee consensus statement on load in sport and risk of injury. *Br J Sports Med, 50*(17), 1030-1041. doi:10.1136/bjsports-2016-096581

Sperlich, B., & Holmberg, H. C. (2017a). The Responses of Elite Athletes to Exercise: An All-Day, 24-h Integrative View Is Required! *Front Physiol, 8*, 564. doi:10.3389/fphys.2017.00564

Sperlich, B., & Holmberg, H. C. (2017b). Wearable, yes, but able...?: it is time for evidence-based marketing claims! *Br J Sports Med, 51*(16), 1240. doi:10.1136/bjsports-2016-097295

Spierer, D. K., Rosen, Z., Litman, L. L., & Fujii, K. (2015). Validation of photoplethysmography as a method to detect heart rate during rest and exercise. *J Med Eng Technol, 39*(5), 264-271. doi:10.3109/03091902.2015.1047536

Bundesinstitut für Sportwissenschaft (2019). „Einsatzgebiete von Künstlicher Intelligenz (KI) im Spitzensport“ Überblick über Anwendungsmöglichkeiten in anderen Bereichen der Wissenschaft oder Wirtschaft und mögliche Synergien für den Spitzensport. Retrieved from https://www.bisp.de/SharedDocs/Downloads/Ausschreibungen/Ausschreibung_Expertise_KI.pdf;jsessionid=D689438C8A7754D817D65BA078382B76.2_cid387?__blob=publicationFile&v=3

Stanley, J., Peake, J. M., & Buchheit, M. (2013). Cardiac parasympathetic reactivation following exercise: implications for training prescription. *Sports Med, 43*(12), 1259-1277. doi:10.1007/s40279-013-0083-4

Starling, L. T., & Lambert, M. I. (2017). Monitoring Rugby Players for Fitness and Fatigue: What Do Coaches Want? *Int J Sports Physiol Perform*, 1-30. doi:10.1123/ijspp.2017-0416

Tanaka, H. (2018). Exercise Nonresponders: Genetic Curse, Poor Compliance, or Improper Prescription? *Exerc Sport Sci Rev, 46*(3), 137. doi:10.1249/JES.0000000000000156

Thompson, W. (2015). Worldwide survey of fitness trends for 2016: 10th Anniversary Edition. *ACSM Health Fitness J, 19,* 9-18. doi:10.1249/FIT.0000000000000164

Thompson, W. (2016). Worldwide survey of fitness trends for 2017. *ACSM Health Fitness J, 20*(6), 8-17. doi:10.1249/FIT.0000000000000252

Thompson, W. R. (2018). Worldwide survey of fitness trends for 2019. *ACSM's Health & Fitness Journal, 22*(6), 10-17.

Thomson, E. A., Nuss, K., Comstock, A., Reinwald, S., Blake, S., Pimentel, R. E., . . . Li, K. (2019). Heart rate measures from the Apple Watch, Fitbit Charge HR 2, and electrocardiogram across different exercise intensities. *J Sports Sci, 37*(12), 1411-1419. doi:10.1080/02640414.2018.1560644

Verghese, A., Shah, N. H., & Harrington, R. A. (2018). What This Computer Needs Is a Physician: Humanism and Artificial Intelligence. *JAMA, 319*(1), 19-20. doi:10.1001/jama.2017.19198

Vogler, A. J., Rice, A. J., & Gore, C. J. (2010). Validity and reliability of the Cortex MetaMax3B portable metabolic system. *J Sports Sci, 28*(7), 733-742. doi:10.1080/02640410903582776

Wahl, Y., Düking, P., Droszez, A., Wahl, P., & Mester, J. (2017). Criterion-Validity of Commercially Available Physical Activity Tracker to Estimate Step Count, Covered Distance and Energy Expenditure during Sports Conditions. *Front Physiol, 8*, 725. doi:10.3389/fphys.2017.00725

Waldrop, M. M. (2016). The chips are down for Moore's law. *Nature*, *530*(7589), 144-147. doi:10.1038/530144a

Weineck, J. (2007). *Optimales Training. Leistungsphysiologishce Trainingslehre unter besonderer Berücksichtigung des Kindes- und Jugendtrainings* (Vol. 15): Spitta Verlag GmbH & Co. Kg.

Wiewelhove, T., Schneider, C., Doweling, A., Hanakam, F., Rasche, C., Meyer, T., . . . Ferrauti, A. (2018). Effects of different recovery strategies following a half-marathon on fatigue markers in recreational runners. *PLoS One, 13*(11), e0207313. doi:10.1371/journal.pone.0207313

Yu, K. H., Beam, A. L., & Kohane, I. S. (2018). Artificial intelligence in healthcare. *Nat Biomed Eng, 2*(10), 719-731. doi:10.1038/s41551-018-0305-z

Zaciorskij, V. (1971). Kybernetik-Mathematik-Sport. *Theorie und Praxis der Körperkultur, 20*(10), 1068-1069.

Zinner, C., Olstad, D. S., & Sperlich, B. (2018). Mesocycles with Different Training Intensity Distribution in Recreational Runners. *Med Sci Sports Exerc*. doi:10.1249/MSS.0000000000001599

III. Methodenanhang

Im Folgenden werden die in den *Studien 1-6* verwendeten Materialien und Messinstrumente spezifiziert und in alphabetischer Reihenfolge aufgeführt.

Material und Messmethodik	Marker	Gerätespezifikation	Hersteller
Amperometrie	- Laktatkonzentration im kapillaren Vollblut [$mmol \cdot l^{-1}$]	Lactate Pro 2	Arkray KDK; Kyoto; Japan
Bioelektrische Impedanzanalyse	- Körpermasse [kg] - Körperfett anteilig in [%] - Körperfett [kg] - Fettfreie Masse [kg]	Tanita BC 418 MA	Tanita Corp.; Tokyo; Japan
Herzfrequenzmessung	- Herzfrequenz [bpm]	Polar V 800	Polar Electro Oy; Kempele; Finnland

Laufband	- Laufgeschwindigkeit [$km \cdot h^{-1}$] - Laufdistanz [m]	Mercurcy	h/p Cosmos; Nussdorf-Traunstein; Deutschland
Spiroergometrie	- Sauerstoffaufnahme [$ml \cdot min^{-1}$] - Atemminutenvolumen [$ml \cdot min^{-1}$] - Energieverbrauch [$kcal \cdot h^{-1}$] - Respiratorischer Quotient [dimensionslos]	MetaMax 3B	Cortex; Leipzig; Deutschland
Sprintfähigkeit	- Distanz [m] - Zeit [s]	Speedcourt	Globalspeed GmbH; Hemsbach; Deutschland
Subjektives Belastungsempfinden	- Borg Skala (6-20)		Borg G. [1970]. Perceived exertion as an indicator of

				somatic stress. Scand J Rehabil Med, 2[2], 92-98.
Wearables	-	Herzfrequenz [bpm]	Polar Vantage V	Polar Electro Oy; Kempele; Finnland
	-	Energieverbrauch [kcal·h^{-1}]		
			Apple Watch Series 4	Apple Inc.; Cupertino; USA
			Garmin Fenix 5	Garmin; Olathe; USA
			Fitbit Versa	Fitbit Inc.; San Francisco; USA

IV. Gesamttexte der *Studien 1,2,3,5,6*.

Der Gesamttext von Studie *4* wird nicht abgedruckt, da die Studie zum Zeitpunkt der Abgabe noch unveröffentlicht ist.

1. **Düking P,** Hotho A, Holmberg HC, Fuss FK, Sperlich B. Comparison of Non-Invasive Individual Monitoring of the Training and Health of Athletes with Commercially Available Wearable Technologies. Frontiers in physiology. 2016;7:71.
2. **Düking P,** Fuss FK, Holmberg HC, Sperlich B. Recommendations for Assessment of the Reliability, Sensitivity, and Validity of Data Provided by Wearable Sensors Designed for Monitoring Physical Activity. JMIR mHealth and uHealth. 2018 Apr 30;6(4):e102.
3. **Düking P,** Holmberg HC, Frenkel MO, Giessing L, Köhler K, Sperlich B. Assessment of the validity of four commercially available wrist-worn wearables for monitoring heart rate and energy expenditure while sitting or performing light-to-vigorous physical activity. JMIR mHealth and uHealth (preprint)
4. **Düking P,** Zinner C, Reed JL, Holmberg HC, Sperlich B. Predefined vs. data guided training prescription based on autonomic nervous system variation: A systematic review. Scandinavian Journal of Medicine and Science in Sports (submitted, 26.02.2020)
5. **Düking P**, Achtzehn S, Holmberg HC, Sperlich B. Integrated Framework of Load Monitoring by a Combination of Smartphone Applications, Wearables and Point-of-Care Testing Provides Feedback that Allows Individual Responsive Adjustments to Activities of Daily Living. Sensors (Basel). 2018 May 19;18(5).

6. **Düking P**, Stammel C, Sperlich B, Sutehall S, Muniz-Pardos B, Lima G, et al. Necessary Steps to Accelerate the Integration of Wearable Sensors Into Recreation and Competitive Sports. Curr Sports Med Rep. 2018 Jun;17(6):178-82.

frontiers in Physiology

REVIEW
published: 09 March 2016
doi: 10.3389/fphys.2016.00071

Comparison of Non-Invasive Individual Monitoring of the Training and Health of Athletes with Commercially Available Wearable Technologies

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Athletes adapt their training daily to optimize performance, as well as avoid fatigue, overtraining and other undesirable effects on their health. To optimize training load, each athlete must take his/her own personal objective and subjective characteristics into consideration and an increasing number of wearable technologies (wearables) provide convenient monitoring of various parameters. Accordingly, it is important to help athletes decide which parameters are of primary interest and which wearables can monitor these parameters most effectively. Here, we discuss the wearable technologies available for non-invasive monitoring of various parameters concerning an athlete's training and health. On the basis of these considerations, we suggest directions for future development. Furthermore, we propose that a combination of several wearables is most effective for accessing all relevant parameters, disturbing the athlete as little as possible, and optimizing performance and promoting health.

Keywords: wearable technologies, performance parameters, health monitoring, performance monitoring, sports technology

OPEN ACCESS

Edited by:
Johnny Padulo,
Università eCampus, Italy

Reviewed by:
Pantelis Theodoros Nikolaidis,
Hellenic Army Academy, Greece
Alessandro Moura Zagatto,
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Specialty section:
This article was submitted to Exercise Physiology, a section of the journal Frontiers in Physiology

Received: *05 January 2016*
Accepted: *15 February 2016*
Published: *09 March 2016*

Citation:
Düking P, Hotho A, Holmberg H-C, Fuss FK and Sperlich B (2016) Comparison of Non-Invasive Individual Monitoring of the Training and Health of Athletes with Commercially Available Wearable Technologies. Front. Physiol. 7:71. doi: 10.3389/fphys.2016.00071

INTRODUCTION

The survey of fitness trends world-wide published in December 2015 (Thompson, 2015) indicates that in 2016 for the first time, wearable technology will become the most popular and leading trend, with the wearable technology market approaching $6 billion dollars. Other trends in fitness, such as body weight training (ranked second in 2016) and high-intensity interval training (ranked sixth) have changed by no more than one place in ranking compared to 2015 (Thompson, 2014). In contrast, in 2015 wearable technology was not ranked at all, probably because it was not even included in the survey.

Adaptation of training is highly individual (Bouchard et al., 1986), depending in part on the balance between exercise and recovery. A suboptimal training load can result in stagnation or de-adaptation, whereas overly intense and/or prolonged training may lead to chronic fatigue, overreaching or overtraining, and negative health effects (Borresen and Lambert, 2009; Buchheit, 2014; Halson, 2014a). In this context, continuous (non-invasive) monitoring of biological and psychological markers might be helpful (Halson, 2014a), and since wearables offer the opportunity to measure different markers conveniently, they provide a promising approach. Wearables are lightweight, sensor-based devices which are worn close to and/or on the surface of the skin, where they detect, analyze, and transmit information concerning several internal and/or external variables to an external device and provide in some cases immediate biofeedback to the athlete. However, the variety of such wearables already available is overwhelming and it is not clear which one(s) may be best for monitoring training and health.

Accordingly, our present aims are threefold: (a) to briefly summarize (non-invasive) parameters that are of potential value in assessing an athlete's training and health; (b) to provide a brief overview of the individual wearables presently available and the parameters they monitor; and (c) to highlight current gaps in our knowledge in order to help direct both future scientific studies and the development of commercial wearables.

CANDIDATE VARIABLES FOR (NON-INVASIVE) MONITORING OF AN ATHLETE'S TRAINING AND HEALTH

Monitoring Training Status

Monitoring of an athlete's training status must take into consideration the external load applied (i.e., the work completed) in relationship to the individual's response to this load, and a recent review has nicely summarized the various internal and external parameters of potential interest in this context (Halson, 2014a). These parameters and their response to training are highly complex and it is beyond the scope of the present review to discuss them in detail. We simply outline key parameters briefly and refer readers interested in more information to other publications (Borresen and Lambert, 2009; Halson, 2014a).

The external load is usually reflected in parameters such as distance (e.g., when running), velocity (e.g., of running), the duration and frequency of training sessions, etc. (Halson, 2014a). In addition, environmental conditions such as altitude, temperature, and relative humidity can influence the external load (Hargreaves, 2008; Mazzeo, 2008; Drust and Waterhouse, 2010; Maughan et al., 2012; Born et al., 2014) and should therefore be monitored as well.

Among the great variety of relevant internal parameters, some can only be monitored with sophisticated instruments and/or are invasive (e.g., blood analysis) and thereby impractical for daily use (Halson, 2014a). From a practical point of view, monitoring of internal parameters should not only be non-invasive, but also efficiently provide daily simple, yet scientifically trustworthy feedback designed to improve performance and maintain health. Examples include heart rate (HR) during exercise (HRex), as well as recovery (HRR) and variability (HRV) of HR (Achten and Jeukendrup, 2003; Buchheit, 2014; Halson, 2014a).

The HRR is defined as the rate of decline in HR following termination of exercise, which is regulated by the autonomic nervous system and thereby provides information concerning sympathetic and parasympathetic activity (Daanen et al., 2012). In general, the more rapid the HRR, the better the fitness (Daanen et al., 2012; Buchheit, 2014). However, since in trained endurance athletes a period of functional overreaching also appears to be associated with more rapid HRR, this parameter must be evaluated in the context of the training schedule (Aubry et al., 2015).

The HRV, defined as the time that elapses between two heart beats (Achten and Jeukendrup, 2003), can reveal alterations in the autonomous nervous system of the heart (Buchheit, 2014). Even though its applicability is debated (Plews et al., 2013; Halson, 2014a), when assessed longitudinally and at specific time-points (during the night or immediately after waking-up) HRV can help reveal an athlete's training and health status (Plews et al., 2013, 2014; Buchheit, 2014).

In addition to these parameters related to the heart, elevated neuromuscular fatigue (defined as a reduction in force generation due either to central and/or peripheral factors) has been associated with symptoms of overtraining and should be monitored frequently (Fowles, 2006; Cormack et al., 2008; Buchheit, 2014).

Moreover, different lactate thresholds are commonly used to determine an athlete's internal loading and can be used to access the results of training interventions (Bellotti et al., 2013; Halson, 2014a). Consequently, in connection with monitoring an athlete's training status, blood levels of lactate should also be taken into consideration.

Monitoring Health Status

Even though the parameters described above are related to those discussed in this section, we highlight here those that provide deeper insight into the training related health status of athletes (Speedy et al., 2001; Halson, 2014b; Saw et al., 2015).

Assessment of hydration status (which is influenced both by the extent of sweating and drinking behavior) is necessary, since dehydration can impair performance and, moreover, is associated with several deleterious health consequences, including heat strokes (Sawka et al., 2007). At the same time, overdrinking can result in hyponatremia and subsequent fatigue, confusion, coma, and even death (Speedy et al., 2001). Consequently, monitoring both fluid loss by sweat and fluid intake is of considerable importance.

When exercising in extreme environments, the athlete's core temperature can exceed 40°C (hyperthermia) or be less than 35° C (hypothermia), which can lead to several kinds of injuries and even threaten life (Armstrong et al., 2007; Fudge et al., 2015).

Ultraviolet (UV) radiation can damage DNA (Cadet et al., 2005) and is a major risk factor for melanoma and other forms of skin cancer (Moehrle, 2008). Consequently, athletes exercising outdoors should monitor their exposure to sunlight, both direct and reflected.

An alteration in the athlete's arterial blood oxygenation (SpO_2) may explain decrements in performance (Siegler et al., 2007), especially at altitudes where this value is lowered, and may also help to predict acute mountain sickness (Basnyat, 2014).

The quality and quantity of sleep, especially slow-wave sleep during which growth hormones are secreted, are important for recovery, performance, and health and should also be monitored (Halson, 2014b). Impaired sleep disrupts cognitive and immune functions, enhances daytime sleepiness, and reduces overall performance (Leeder et al., 2012; Halson, 2014b).

Subjective parameters, such as mood disturbances or perceived stress and inadequate recovery, can be assessed with different questionnaires that actually appear to provide a more sensitive and consistent evaluation of an athlete's well-being and training load than objective markers (Saw et al., 2015). Accordingly, such questionnaires should be applied with confidence in daily practice (Saw et al., 2015).

WEARABLE TECHNOLOGIES DESIGNED FOR INDIVIDUAL CONSUMERS

To evaluate how wearables may assist in monitoring an athlete's training and health, the technologies involved and their abilities to detect specific parameters must be understood.

Several wearables can calculate or estimate body position, movement velocity, distance traveled, and acceleration employing information provided by Global Navigation Satellite Systems (GNSS; such as the Global Positioning System; GPS) (Schutz and Chambaz, 1997; Cummins et al., 2013). With this technology, a good line-of-sight and high-sampling frequency are important for obtaining accurate data (Baranski and Strumillo, 2012; Cummins et al., 2013). Consequently, GNSS measurements do not function indoors or underwater and, moreover, their accuracy may be compromised in densely built-up areas. Inexpensive GPS systems are latent, a problem avoided by high-frequency sampling by professional systems. In contrast, speed tracking appears to be accurate even with inexpensive systems. Position, velocity and distance measured at low-to-moderate velocities ($<$20 km$\cdot$h^{-1}) by such systems are also reliable, but acceleration data are prone to error and should be interpreted with caution (Cummins et al., 2013; Buchheit et al., 2014).

Accelerometers, which are commonly piezoelectric, piezoresistive, capacitive, or based on strain gauges (Kavanagh and Menz, 2008; Yang and Li, 2012), are used to quantify the distance an athlete covers during training, as well as to evaluate total sleep time and estimate sleep quality, thereby providing an estimate of the quality of sleep (Halson, 2014a). Distance is derived by most accelerometers from the number of steps taken and most count accurately at velocities $>$67 m$\cdot$min^{-1} (1.12 m$\cdot$s^{-1}) (Feito et al., 2012), which, however, does not necessarily mean that they measure distance accurately. Accelerometers are reasonably reliable and valid for monitoring the quality and quantity of sleep in certain populations with an accuracy of 80% compared to polysomnography (Leeder et al., 2012; Hausswirth et al., 2014). However, each accelerometer must be fitted securely to prevent motion artifacts (Yang and Hsu, 2010) and accelerometers often fail in detecting the state of wakefulness in sleep periods. Therefore, other methods for the purpose of sleep monitoring are warranted (Sadeh, 2011).

Pulse oximetry exploits the fact that oxyhemoglobin and deoxyhemoglobin absorb near-infrared light maximally at different wavelengths to monitor the oxygen saturation of arterial blood continuously (Chan and Chan, 2013). These sensors are inexpensive, small and simple to use (Chan and Chan, 2013), but prone to potential error due to vasoconstriction, hypovolemia and artifacts caused by excessive movement (Chan and Chan, 2013; Windsor and Rodway, 2014), which limits their usefulness in cold environments and while exercising.

Parameters associated with HR can be monitored with chest belts, photoplethysmography, or various sensors incorporated into clothing. Although chest belts are widely used by athletes, they are experienced as uncomfortable (Buchheit, 2014; Spierer et al., 2015). Photoplethysmography involves a diode on the skin that emits red or near-infrared light that penetrates the underlying tissue and is then reflected back and detected by a photo sensor. This allows assessment of pulse rate with sufficient accuracy at rest, but the error of measurement can be dependent on the photosensitivity of the skin and increases during exercise due to motion artifacts (Schäfer and Vagedes, 2013; Spierer et al., 2015). Consequently, such data should be interpreted with caution. In the case of smart clothing, conducting or metal-coated fibers can be woven into the fabric or conducting inks can be printed onto the garment to monitor HR and associated parameters (Stoppa and Chiolerio, 2014). However, even though promising, only a few studies to date have evaluated the accuracy and reliability of smart clothing (Pandian et al., 2008; Curone et al., 2010) and more are warranted.

To monitor muscle activity by electromyography (EMG), electrodes woven into fabrics have been found to provide values similar to those obtained with traditional surface electrodes (Finni et al., 2007). The drawback of skin electrodes, however, is that

- they must be positioned accurately, preferably "in the midline of the muscle belly between the nearest innervation zone and the myotendinous junction furthest from this zone" (De Luca, 1997), since even small movements away from the innervation zone (e.g., 10% of the muscle length) reduce signal amplitude considerably (Belbasis and Fuss, 2015);
- they must have a tri-polar configuration to allow utilization of "the double differential technique to eliminate the presence of crosstalk" (De Luca, 1997) between different muscles; and
- the signal-force relationship is non-linear and dependend on the number of motor units recruited in the vicinity of the electrode (De Luca, 1997).

Therefore, EMG fabrics designed to assess muscular activity are considered inaccurate. An alternative and promising approach involves incorporation of pressure sensors into compression garments (Belbasis and Fuss, 2015).

To access local muscle oxidative metabolism and to derive lactate thresholds non-invasively, devices which use near-infrared spectroscopy (NIRS) can be employed (Ferrari et al., 2004; Bellotti et al., 2013). These devices are efficient in terms of both time and cost (Bellotti et al., 2013), but are disturbed by adipose tissue (Ferrari et al., 2004) and motion artifacts (Virtanen et al., 2011).

OVERVIEW OF COMMERCIALLY AVAILABLE WEARABLE TECHNOLOGIES DESIGNED FOR USE BY ATHLETES

The present discussion here is based on information provided by the manufacturers on their websites. Since the list of available wearables is large and rapidly growing, those described here were chosen if the technology involved was indicated on the website and if they appeared to be the most advanced product of a given manufacturer for a specific purpose. Moreover, we focus solely on wearables that show promise for monitoring the training and health of athletes.

We summarize the wearables chosen ($n = 36$) in **Table 1** [wrist-worn devices ($n = 22$)], **Table 2** [clothing-based ($n = 8$)], and **Table 3** [ear-worn ($n = 4$) and other devices ($n = 3$)], together with the parameters of interest which they monitor and the technology on which they are based. All of these wearables transmit the data they collect to an external device for further analysis and most provide immediate biofeedback to the athlete. So far the accuracy, reliability, or validity of nine devices have been evaluated scientifically (for details please see **Tables 1–3**).

Wrist-Worn Devices

Most wrist-worn devices employ accelerometers ($n = 16$), gyroscopes ($n = 3$), GNSS ($n = 8$), (barometric) altimeters ($n = 8$), photoplethysmography ($n = 8$), additional chest belts ($n = 8$), sensors of skin temperature ($n = 4$), pulse oximeters ($n = 2$) and/or sensors of UV light ($n = 1$) to monitor duration of activity ($n = 21$), distance ($n = 17$), and velocity ($n = 12$) of an athlete's locomotion, change in elevation ($n = 10$), environmental temperature ($n = 1$), altitude ($n = 2$), HR ($n = 19$), HRV ($n = 2$), neuromuscular fatigue ($n = 1$), UV radiation ($n = 1$), SpO_2 ($n = 3$), sleep quality and quantity ($n = 14$), and subjective markers ($n = 1$). However, HR recovery, humidity, hydration status, lactate thresholds and body temperature are not assessed. Furthermore, the only wearable that accesses subjective markers focuses on pain, but no other factors related to the training and health status of athletes.

The previous model of the Philips Actiwatch Spectrum Pro© (Philips Respironics, Murrysville, PA, USA) showed high accuracy to detect sleep compared to polysomnography, however, its ability to detect wakefulness is low (Marino et al., 2013).

The preceding model of the Withings Pulse Ox© (Withings SA, Issy-les-Moulineaux, France) overestimates sleep time with a validity of $r = 0.92$ compared to polysomnography (Ferguson et al., 2015).

The Polar V800 (Polar Electro, Kempele, Finland) is valid to detect RR intervals with an error of 0.09% and an intra-class correlation coefficient of >0.99 (Giles et al., 2016).

The preceding model of the Mio Alpha 2© gave HR values while walking, weight lifting, and biking that differed significantly from those obtained with a reference device and this model appears to be prone to motion artifacts (Spierer et al., 2015).

The Jawbone UP © (the model preceding the Jawbone UP3 we describe) was validated for measurement of total sleep time and time-point of awakening after sleep onset and showed good agreement with polysomnography (de Zambotti et al., 2015).

To the best of our knowledge all other devices have not been evaluated scientifically and, accordingly, the data they provide should be interpreted with considerable caution.

Devices Incorporated into Clothing

Specially designed ("smart") clothing, ranging from shirts, shorts, hats/helmets to socks, can monitor several internal and external parameters of relevance to athletes. Most "smart" clothing currently available utilizes accelerometers ($n = 5$), electrocardiography ($n = 1$), additional chest belts ($n = 1$), photoplethysmography ($n = 2$), and/or conducting fibers woven into the fabric ($n = 2$) to measure HR ($n = 7$), HR recovery ($n = 2$), HR variability ($n = 2$), neuromuscular fatigue (by EMG, $n = 1$), and lactate threshold (by NIRS, $n = 1$). To assess the external parameters duration ($n = 3$), distance ($n = 2$), velocity ($n = 2$), and change in elevation ($n = 1$), "smart" clothes (with exception of the Zephyr BioHarness™ 3) rely on the data transmitted by the companion smartphone. The BioHarness™ 3 (Zephyr Technology Corp, Annapolis, USA) also aims to derive body temperature from the parameters it assesses (Zephyr Technology Corp, 2015). To date, environmental temperature, humidity, UV radiation, SpO_2, hydration status, quantity and quality of sleep, and subjective factors have been neglected by designers of "smart" clothing. Furthermore, no "smart" clothing presently available can provide immediate biofeedback to the athlete without the involvement of an external device.

The Hexoskin© vest (Carré Technologies Inc., Montreal, Québec Canada) provides reliable detection of an athlete's HR when lying, sitting, standing or walking slowly (%CV $< 0.79 \pm 0.77$; ICC > 0.96; Villar et al., 2015). However, measurement of the other parameters relevant to the training and health of athletes has not yet been validated, least of all when training.

The BioHarness™ 3 has an acceptable level of validity and reliability for HR ($r = \sim 0.91$, $p < 0.01$; %CV < 7.6), but increasing errors at higher velocity (Johnstone et al., 2012). Measurement of HRR and HRV by this device has not been evaluated scientifically. Since, at least to our knowledge, no other form of "smart" clothing has yet been evaluated scientifically, the data they provide should be interpreted with due caution.

Ear-Worn Devices

Devices worn as an earplug ($n = 3$) or around the auricle ($n = 1$) use accelerometers ($n = 3$), pulse oximeters ($n = 2$), photoplethysmography ($n = 2$), temperature sensors ($n = 1$), gyroscopes, and magnetometers ($n = 1$) to assess duration ($n = 3$), distance covered by the athlete while training ($n = 1$), velocity ($n = 1$), HR ($n = 4$), HRV ($n = 1$), HRR ($n = 1$), SpO_2 ($n = 3$), and body temperature ($n = 1$). However, it should be noted that such devices measure variations in pulse rate rather than HRV directly (Schäfer and Vagedes, 2013). Parameters such as change in elevation, environmental temperature, humidity, altitude, neuromuscular fatigue, UV radiation, hydration status, lactate

TABLE 1 | Wrist devices designed to monitor parameters related to the training and health of athletes.

Device	Training parameters monitored	Health parameters monitored	Technology employed	Additional comments and scientific evaluation
Polar V800© (Polar Electro, 2015)	D, L, V, El, Alt, HR, HRR, HRV, F	Slt, Slq	GPS, HR chestbelt, additional sensors	Additional Sensors from Polar Electro required. Valid to detect RR intervals with an error of 0.09% and an ICC > 0.99 (Giles et al., 2016)
Microsoft Band 2© (Microsoft, 2015)	D, L, V, HR	UV, Slt, Slq	Accelerometer, ambient light sensor, barometer, capacitive sensor, GPS, GSR, gyroscope, photoplethysmograph, skin temp. sensor, UV sensor	
amiigo© (Amiigo, 2015)	D, L, V, HR, (HRV)	Oxy, Slt, Slq	Accelerometer, pulse oximeter, temp. sensor	
Fitbit Surge© (fitbit Inc., 2015b)	D, L, V, El, HR	Slt, Slq	Accelerometer, altimeter, digital compass, GPS, gyroscope, photoplethysmograph, ambient light sensor	
Suunto Ambit3 Peak (HR) (Suunto, 2015)	D, L, V, El, Etemp, Alt, HR		GPS, barometer, compass, HR chestbelt	
Withings Pulse Ox© (Withings, 2015)	D, L, El, HR	Oxy, Slt, Slq	Accelerometer, pulse oximeter	The preceding model overestimates sleep time, but had a validity of $r = 0.92$ when compared to a gold standard (Ferguson et al., 2015)
Fitbit charge HR© (fitbit Inc., 2015a)	D, L, El, HR	Slt, Slq	Accelerometer, altimeter, photoplethysmograph	
Garmin vivoactive© (Garmin Ltd., 2015b)	D, L, V, HR	Slt, Slq	Accelerometer, GPS, GLONASS, HR chestbelt	
Garmin vivosmart HR© (Garmin Ltd., 2015c)	D, L, El, HR	Slt, Slq	Accelerometer, altimeter, photoplethysmograph	
Fitbit charge© (fitbit Inc., 2015b)	D, L, El	Slt, Slq	Accelerometer, altimeter	
Garmin Forerunner 910XT© (Garmin Ltd., 2015a)	D, L, V, El, HR		Altimeter, GPS, HR chestbelt	
LG Electronics Lifeband Touch ActivityTracker© (LG Electronics, 2015)	D, L, V, El, HR		Accelerometer, altimeter, HR chestbelt	
Basis Peak© (Basis, 2015)	D, HR	Slt, Slq	Accelerometer, photoplethysmograph, GSR, skin temp. sensor	
Jawbone UP3© (Jawbone, 2015)	D, HR	Slt, Slq	Accelerometer, bioimpedence Sensor	For total sleep time, sleep efficiency, and wake after sleep onset, the preceding model showed good agreement with polyssomnography with a mean difference ± SD of 10.0 ± 20.5 min; −1.9 ± 4.2% and 0.6 ± 14.7 min, respectively (de Zambotti et al., 2015).

(Continued)

TABLE 1 | Continued

Device	Training parameters monitored	Health parameters monitored	Technology employed	Additional comments and scientific evaluation
Mio Alpha 2© (Mio Global, 2015)	D, L, V, HR		Accelerometer, photoplethysmograph	Its previous model showed significant differences to a reference device for measuring HR at walking, biking ($p < 0.05$) and weight lifting ($p < 0.01$) (Spierer et al., 2015).
Adidas micoach smart run© (adidas Pty. Ltd., 2014)	D, L, V, HR		GPS, photoplethysmograph	
Nike + Sportband© (+Shoe insert) (Nike Inc., 2015a)	D, L, V, HR		HR chestbelt, piezoelectric embed in shoe	
Nike + Sportwatch GPS© (Nike Inc., 2015b)	D, L, V, HR		GPS, HR chestbelt	
Medisana ViFit connect Activity Tracker© (Medisana, 2015)	D, L	Slt, Slq	Accelerometer	
Philips Actiwatch Spectrum Pro© (Philips, 2016)		Slt, Slq, (Sub)	Accelerometer, irradiance sensor, photopic illuminance sensor, Photon Flux sensor	Subjective markers to assess pain only. The sleep accuracy of the preceding modelwas $r = 0.86$ compared to polysomnography (Marino et al., 2013).
Polar Electro Loop©(Polar Electro, 2015)	D, HR	Slt, Slq	Accelerometer, HR chestbelt	
Seraphim Sense Angel Sensor© (Seraphim Sense Ltd., 2014)	D, HR	(Oxy)	Accelerometer, gyroscope, photoplethysmograph, skin temp. sensor	Blood oxygen sensor under development

Abbreviations: Alt, altitude; D, distance traveled; El, change in elevation; Etemp, environmental temperature; F, neuromuscular fatigue; GLONASS, Global Navigation Satellite System; GPS, General Positioning System; GSR, Galvanic Skin Response; HR, heart rate; HRV, variability of heart rate; HRR, heart rate recovery; ICC, Intraclass correlation coefficient; L, duration of exercise; Oxy, blood oxygenation; Slq, sleep quality; Slt, sleep time; Sub, subjective markers; UV, ultraviolet radiation; V, velocity; (), with restrictions.

TABLE 2 | Clothing-based wearables designed to monitor parameters related to the training and health of athletes.

Device	Training parameters monitored	Health parameters monitored	Technology employed	Additional comments and scientific evaluation
Zephyr Technology Corp. BioHarness^{TM} 3 (Zephyr Technology Corp, 2015)	L, V, HR, HRR, HRV		Accelerometer, GPS, HR sensors woven into fabric	Aims to estimate core temperature by other parameters. HR measurement was reliable ($r = \sim 0.91$, $p < 0.01$, $CV < 7.6$) and precise ($r = 0.61–0.67$, $p < 0.01$) when participants performed a walk-jog-run protocol; error increases with increasing velocity (Johnstone et al., 2012).
Carré Technologies Inc. Hexoskin© (Carrè Technologies Inc., 2015)	(D), HR, HRR; HRV		Accelerometer, expansion belts, three point ECG	Not specified if Hexoskin vest or smartphone App measures the parameter duration. The HR measurements showed low CV (%) of < 0.79 ±0.77 and high ICC of >0.96 at different walking speeds (Villar et al., 2015).
Myontec MBody Bike&Run© (Myontec Ltd., 2015)	(D), (L), (V), HR, (F)		EMG, HR chestbelt	EMG technology not further specified, GPS from Smartphone
Ralph Lauren the Polotech Shirt©(Ralph Lauren Media LLC, 2015)	(D), HR		Accelerometer, silver fabrics woven into shirt	
LifeBEAM Smart Hat©(LifeBEAM)	HR		Accelerometer, photoplethysmograph	
LifeBeam Smart Helmet©(LifeBEAM)	HR		Accelerometer, photoplethysmograph	
BSXinsight XR2©(BSXinsight)	Lac		NIRS	

Abbreviations: CV, coefficient of variation; D, distance traveled; ECG, Electrocardiogram; EMG, Electromyography; F, neuromuscular fatigue; GPS, General Positioning System; HR, heart rate; HRV, variability of heart rate; HRR, heart rate recovery; ICC, Intraclass correlation coefficient; Lac, lactate threshold; L, duration of exercise; Slq, sleep quality; Slt, sleep time; V, velocity; (), with restrictions.

thresholds, quantity and quality of sleep, as well as subjective markers cannot yet be monitored by ear-worn wearables.

Other Devices

A number of other devices are designed to be worn on specific parts of the body. The BodyMedia Fit© armbands (BodyMedia Inc., Pittsburgh, PA, USA), designed to measure energy turnover, are worn on the upper arm and use an accelerometer in combination with sensors of sweating (the galvanic skin response, GSR), heat flux and skin temperature to recognize motion and thereby monitor an athlete's quantity and quality of sleep, in addition to other parameters not directly relevant to training and health (BodyMedia Inc, 2014). This system calculates the energy expenditure associated with various physical activities reliably (Lee et al., 2014).

The Misfit Shine© (Misfit Wearables, Burlingame, CA, USA) monitors distance, as well as the quantity and quality of sleep with an accelerometer. It can be worn anywhere on the body and transfers the data collected solely to an external device (Wearables). The sleep time measured by Misfit Shine© correlates well to that provided by a reference device, although with some overestimation (Ferguson et al., 2015). No other parameters are monitored.

The Catapult Optimeye S5© (Catapult Innovations, Melbourne, VIC, Australia) utilizes GPS, GLONASS (the Russian equivalent of the American GPS), an accelerometer and gyroscope to track duration, distance, and velocity. This device is worn in a specially designed vest below the neck (Catapult innovations, 2015). The previous model was shown to be valid for determining distance (Johnston et al., 2014), as well as sensitive for assessing velocity (Varley et al., 2012). However, the reliability of these devices is less at short distances or with increasing speed and appears to depend on the sampling frequency (Jennings et al., 2010).

RECOMMENDATIONS CONCERNING WEARABLES FOR ATHLETES

As indicated above, most of the wearables currently available have not yet been evaluated scientifically, even though evaluation of their reliability, validity and accuracy at the very least, particularly in connection with training, is critical for athletes to be able to use them with confidence.

In addition to movement artifacts, the frequency of sampling by a wearable may compromise the quality of the data collected. Although a low frequency may be adequate when the athlete is at rest, a higher frequency is required during exercise when parameter values alter relatively quickly. Scientific evaluation can help determine a sampling frequency that provides sufficient accurate feedback to the athlete, while still being manageable by the storing and processing capacities of the wearable.

In light of these considerations, we strongly advice manufacturers of wearables to arrange for independent scientific evaluation of their products and to base future development on such information.

TABLE 3 | Ear devices and other wearables designed to monitor parameters related to the training and health of athletes.

Device	Training parameters monitored	Health parameters monitored	Technology employed	Additional comments and scientific evaluation
EAR DEVICES				
FreeWavz© (FreeWavz)	L, V, HR	Oxy	Accelerometer, pulse oximeter	Functions as a music player
Cosinuss One© (cosinuss, 2015)	(D), HR, HRV	(Oxy), Btemp	Photoplethysmograph, temp. sensor	Blood oxygenation sensor under development
Lumafit© (Lumafit, 2015)	D, HR, HRR		Accelerometer, photoplethysmograph	Duration via a Smartphone App
Bragi The Dash© (Bragi, 2015)	D,HR	Oxy	Accelerometer, gyroscope, magnetometer, pulse oximeter	Functions as a music player
OTHER DEVICES				
BodyMedia Fit© (BodyMedia Inc, 2014)		Slt, Slq	Accelerometer, GSR, heat flux, skin temp.	Worn on the upper arm, designed to measure energy expenditure
Catapult Optimeye S5© (Catapult innovations, 2015)	D, L, V		Accelerometer, GPS, GLONASS, gyroscope	Worn in a specially design vest. The catapult model is reliable (TEM: 1.3%) and valid for measuring distance with compromised data when the sampling frequency is low (i.e., 1–5 Hz), athletes speed increases and/or at short distances (Jennings et al., 2010; Johnston et al., 2014). The accuracy of accessing velocity has a CV of 3.1–11.3%for the 10 Hz unit (Varley et al., 2012)
Misfit Shine© Misfit Wearables	L	Slt, Slq	Accelerometer	Can be worn anywhere on the body

Abbreviations: Btemp, body temperature; D, distance traveled; GPS, General Positioning System; GSR, Galvanic Skin Response; GLONASS, Global Navigation Satellite System; HR, heart rate; HRV, variability of heart rate; HRR, heart rate recovery; L, duration of exercise; Oxy, blood oxygenation; Slq, sleep quality; Slt, sleep time; TEM, typical error of measurement; V, velocity; (), with restrictions.

Most wearables focus on monitoring duration ($n = 28$), distance ($n = 22$), velocity ($n = 16$) and sometimes changes in elevation ($n = 11$), in combination with the HR ($n = 30$) and sleep ($n = 16$). Environmental temperature ($n = 1$), altitude ($n = 2$), HRV ($n = 5$), HRR ($n = 3$), neuromuscular fatigue ($n = 2$), lactate thresholds ($n = 1$), UV radiation ($n = 1$), and body temperature ($n = 1$) can be assessed by a few; whereas humidity, hydration status, and subjective factors relevant to training and health are completely neglected by all. Therefore, we strongly advise manufacturers to develop devices capable of monitoring such parameters as well.

Measurement of environmental parameters such as temperature, altitude, UV radiation, and humidity is relatively straightforward and should become standard in future wearables.

HRR can be derived from HR, which many of the wearables discussed here can monitor, so that all that is required in this case is additional software. HRV can be derived from variations in pulse rate at rest, so that wearables might focus on this parameter, which is probably easier to access.

Neuromuscular fatigue (at least for the legs) as reflected in a countermovement jump (Cormack et al., 2008) while wearing a low-cost and pressure-sensitive insole (Tan et al., 2015) or a compression garment equipped with pressure sensors could be assessed (Belbasis and Fuss, 2015).

Only one wearable presently available to consumers is able to measure lactate thresholds (via NIRS), and this device focuses on the muscles of the lower leg only. To obtain a more complete picture, it would be desirable to apply NIRS to other groups of muscles as well.

An athlete's hydration status is influenced by how much he/she sweats and this should to be assessable by wearables. The textile sensors developed in connection with the BIOTEX project are already able to determine this, as well as the level of sodium in the sweat (Coyle et al., 2010).

Another sensor designed to assess hydration status appears to be close to being introduced onto the market. In 2015 a transdermal sensor that analyses electrolytes in sweat was developed by the University of Strathclyde. This device provides real-time analysis of fluid loss, with feedback to the user via smart phone, to encourage proper rehydration (University of Strathclyde, 2015).

To the best of our knowledge, no wearables incorporate assessment of subjective factors associated with training and health. This is surprising, since subjective measures have been shown to be superior to objective markers in this context (Saw et al., 2015) and it should be simple to incorporate questionnaires into the software of external devices. One of the subjective variables most commonly monitored in connection with studies on exercise physiology is the "rating of perceived exertion" (RPE) first described by Borg (Borg, 1970), which has proven to be highly sensitive for evaluating general fatigue from different types of exercise (Grant et al., 1999). It is remarkable that the RPE, an easy accessible variable, has not yet been incorporated into any wearable.

However, since monitoring certain parameters requires placement of a device at a specific anatomical location, monitoring of all parameters of interest may not be achievable with a single wearable. For example, body temperature is measured ideally with an ear-worn device, hydration status based on the extent of sweating is best evaluated by clothing which covers as much of the skin as possible; and it is preferable to monitor sleep with a wearable worn on the wrist. At the same time, bearing several different wearables simultaneously might be cumbersome.

Luckily, not all parameters appear to be equally relevant at any given time. For example, HRV is measured ideally during the nighttime or upon waking up (Buchheit, 2014), whereas the hydration status of an athlete is of primary concern before, during and after exercise. Consequently, in order to assess all relevant parameters at the time when they are of most interest while disturbing the athlete as little as possible, it might be of interest to develop a commercial monitoring system composed of different wearables placed at their ideal locations.

Nonetheless, even when wearables provide appropriate and reliable daily feedback to the athlete, these data are interpreted either by the athlete him/herself and/or the algorithm in the manufacturer's software, rather than by professionals, which may lead to inappropriate adjustments in training. Furthermore, the wearables presently available are restricted to non-invasive parameters and without at least minimal assessment of invasive parameters, such as the levels of substances in capillary blood and saliva (e.g., cortisol or immunoglobulin A, creatine kinase, urea, and other markers of immune function and muscle damage), the information provided may be incomplete. Thus, manufacturers of wearables should focus on convenient and rapid measurement of such parameters as well.

Wearables are becoming less and less expensive and more and more athletes are monitoring their health and training and storing this information centrally. This information can be used not only for optimizing individual training, but also for more general (and global) analysis employing data mining, machine learning, and statistical methods. For example, weak signals concerning patterns of movement such as walking, running, climbing stairs, sitting, etc., from a simple sensor could be uploaded into the cloud for analysis. Moreover, typical patterns of behavior in athletic scenarios, such as training camps in and off season, could be identified. The resulting insights could then be used in the development of wearables that provide even better assessment of training and health. However, uploading intimate personal data to unsecure servers and potential commercial use of such data are of considerable concern with respect to individual privacy.

CONCLUSION

In summary, wearables designed to monitor a variety of non-invasive parameters must be evaluated scientifically before these can be confidently employed to assess the training and health status of athletes. Otherwise, the athlete should be skeptical about the usefulness of a wearable in practice.

Furthermore, certain important parameters are completely ignored by today's wearables, even though effective approaches to measuring these parameters are already available. Since monitoring training and health is rather complex, requiring that several parameters be evaluated at different times of the day and on different parts of the body, we propose that a combination of wearables is needed to obtain an overall picture while disturbing the athlete as little as possible. This would help athletes to improve their performance and reduce the risk of injuries from exercise and training.

AUTHOR CONTRIBUTIONS

All authors listed, have made substantial, direct and intellectual contribution to the work, and approved it for publication.

REFERENCES

Achten, J., and Jeukendrup, A. E. (2003). Heart rate monitoring: applications and limitations. *Sports Med.* 33, 517–538. doi: 10.2165/00007256-200333070-00004

adidas Pty. Ltd. (2014). *Adidas Micoach Smart Run.* Retrieved from: http://www.adidas.com.au/micoach-smart-run/G76792.html (Accessed October 22, 2015).

Amiigo (2015). *Features.* Retrieved from: https://amiigo.com/features (Accessed October 22, 2015).

Armstrong, L. E., Casa, D. J., Millard-Stafford, M., Moran, D. S., Pyne, S. W., and Roberts, W. O. (2007). American College of Sports Medicine position stand. Exertional heat illness during training and competition. *Med. Sci. Sports Exerc.* 39, 556–572. doi: 10.1249/MSS.0b013e31802fa199

Aubry, A., Hausswirth, C., Louis, J., Coutts, A. J., Buchheit, M., and Le Meur, Y. (2015). The development of functional overreaching is associated with a faster heart rate recovery in endurance athletes. *PLoS ONE* 10:e0139754. doi: 10.1371/journal.pone.0139754

Baranski, P., and Strumillo, P. (2012). Enhancing position accuracy in urban terrain by fusing data from GPS receiver, inertial sensors, stereo-camera and digital maps for pedestrian navigation. *Sensors* 12, 6764–6801. doi: 10.3390/s120606764

Basis (2015). *Basis Peak.* Retrieved from: http://www.mybasis.com/ (Accessed October 22, 2015).

Basnyat, B. (2014). Pro: pulse oximetry is useful in predicting acute mountain sickness. *High Alt. Med. Biol.* 15, 440–441. doi: 10.1089/ham.2014.1045

Belbasis, A., and Fuss, F. K. (2015). Development of next-generation compression apparel. *Proc. Technol.* 20, 85–90. doi: 10.1016/j.protcy.2015.07.015

Bellotti, C., Calabria, E., Capelli, C., and Pogliaghi, S. (2013). Determination of maximal lactate steady state in healthy adults: can NIRS help? *Med. Sci. Sports Exerc.* 45, 1208–1216. doi: 10.1249/MSS.0b013e3182828ab2

BodyMedia Inc (2014). *The Science.* Retrieved from: http://www.bodymedia.com/the_science.html#&whence=

Borg, G. (1970). Perceived exertion as an indicator of somatic stress. *Scand. J. Rehabil. Med.* 2, 92–98.

Born, D. P., Hoppe, M. W., Lindner, N., Freiwald, J., Holmberg, H. C., and Sperlich, B. (2014). Adaptive mechanisms and behavioural recommendations: playing football in heat, cold and high altitude conditions. *Sportverletz. Sportschaden* 28, 17–23. doi: 10.1055/s-0034-1366055

Borresen, J., and Lambert, M. I. (2009). The quantification of training load, the training response and the effect on performance. *Sports Med.* 39, 779–795. doi: 10.2165/11317780-000000000-00000

Bouchard, C., Lesage, R., Lortie, G., Simoneau, J. A., Hamel, P., Boulay, M. R., et al. (1986). Aerobic performance in brothers, dizygotic and monozygotic twins. *Med. Sci. Sports Exerc.* 18, 639–646. doi: 10.1249/00005768-198612000-00006

Bragi (2015). *The Dash.* Retrieved from: http://www.bragi.com/ (Accessed October 23, 2015).

Buchheit, M. (2014). Monitoring training status with HR measures: do all roads lead to Rome? *Front. Physiol.* 5:73. doi: 10.3389/fphys.2014.00073

Buchheit, M., Al Haddad, H., Simpson, B. M., Palazzi, D., Bourdon, P. C., Di Salvo, V., et al. (2014). Monitoring accelerations with GPS in football: time to slow down? *Int. J. Sports Physiol. Perform.* 9, 442–445. doi: 10.1123/IJSPP.2013-0187

Cadet, J., Sage, E., and Douki, T. (2005). Ultraviolet radiation-mediated damage to cellular DNA. *Mutat. Res.* 571, 3–17. doi: 10.1016/j.mrfmmm.2004.09.012

Carrè Technologies Inc. (2015). *Hexoscin.* Retrieved from: http://www.hexoskin.com/ (Accessed February 25, 2016).

Catapult innovations. (2015). *Optimeye S5*. Retrieved from: http://www.catapultsports.com/au/system/outdoor

Chan, E. D., and Chan, M. M. (2013). Pulse oximetry: understanding its basic principles facilitates appreciation of its limitations. *Respir. Med.* 107, 789–799. doi: 10.1016/j.rmed.2013.02.004

Cormack, S. J., Newton, R. U., and McGuigan, M. R. (2008). Neuromuscular and endocrine responses of elite players to an Australian rules football match. *Int. J. Sports Physiol. Perform.* 3, 359–374.

cosinuss (2015). *cosinuss One.* Retrieved from: http://www.cosinuss.com/en/ (Accessed October 23, 2015).

Coyle, S., Lau, K. T., Moyna, N., O'Gorman, D., Diamond, D., Di Francesco, F., et al. (2010). BIOTEX–biosensing textiles for personalised healthcare management. *IEEE Trans. Inf. Technol. Biomed.* 14, 364–370. doi: 10.1109/TITB.2009.2038484

Cummins, C., Orr, R., O'Connor, H., and West, C. (2013). Global positioning systems (GPS) and microtechnology sensors in team sports: a systematic review. *Sports Med.* 43, 1025–1042. doi: 10.1007/s40279-013-0069-2

Curone, D., Secco, E. L., Tognetti, A., Loriga, G., Dudnik, G., Risatti, M., et al. (2010). Smart garments for emergency operators: the ProeTEX project. *IEEE Trans. Inf. Technol. Biomed.* 14, 694–701. doi: 10.1109/TITB.2010.2045003

Daanen, H. A., Lamberts, R. P., Kallen, V. L., Jin, A., and Van Meeteren, N. L. (2012). A systematic review on heart-rate recovery to monitor changes in training status in athletes. *Int. J. Sports Physiol. Perform.* 7, 251–260.

De Luca, C. J. (1997). The use of surface electromyography in biomechanics. *J. Appl. Biomech.* 13, 135–163.

de Zambotti, M., Baker, F. C., and Colrain, I. M. (2015). Validation of sleep-tracking technology compared with polysomnography in adolescents. *Sleep* 38, 1461–1468. doi: 10.5665/sleep.4990

Drust, B., and Waterhouse, J. (2010). Exercise at altitude. *Scott. Med. J.* 55, 31–34. doi: 10.1258/rsmsmj.55.2.31

Feito, Y., Bassett, D. R., and Thompson, D. L. (2012). Evaluation of activity monitors in controlled and free-living environments. *Med. Sci. Sports Exerc.* 44, 733–741. doi: 10.1249/MSS.0b013e3182351913

Ferguson, T., Rowlands, A. V., Olds, T., and Maher, C. (2015). The validity of consumer-level, activity monitors in healthy adults worn in free-living conditions: a cross-sectional study. *Int. J. Behav. Nutr. Phys. Act.* 12, 1–9. doi: 10.1186/s12966-015-0201-9

Ferrari, M., Mottola, L., and Quaresima, V. (2004). Principles, techniques, and limitations of near infrared spectroscopy. *Can. J. Appl. Physiol.* 29, 463–487. doi: 10.1139/h04-031

Finni, T., Hu, M., Kettunen, P., Vilavuo, T., and Cheng, S. (2007). Measurement of EMG activity with textile electrodes embedded into clothing. *Physiol. Meas.* 28, 1405–1419. doi: 10.1088/0967-3334/28/11/007

fitbit Inc. (2015a). *ChargeHR*. Retrieved from: www.fitbit.com/au/chargehr (Accessed October 22, 2015).

fitbit Inc. (2015b). *Surge.* Retrieved from: www.fitbit.com/au/surge (Accessed October 22, 2015).

Fowles, J. R. (2006). Technical issues in quantifying low-frequency fatigue in athletes. *Int. J. Sports Physiol. Perform.* 1, 169–171.

Fudge, J. R., Bennett, B. L., Simanis, J. P., and Roberts, W. O. (2015). Medical evaluation for exposure extremes: cold. *Clin. J. Sport Med.* 25, 432–436. doi: 10.1097/JSM.0000000000000224

Garmin Ltd. (2015a). *Forerunner 910XT*. Retrieved from: https://buy.garmin.com/en-AU/AU/wearabletech/watches-wearable-technology/forerunner-910xt/prod90671.html (Accessed October 22, 2015).

Garmin Ltd. (2015b). *Vivoactive.* Retrieved from: https://buy.garmin.com/en-US/US/prod150767.html (Accessed October 22, 2015).

Garmin Ltd. (2015c). *vivosmart HR.* Retrieved from: https://buy.garmin.com/en-US/US/into-sports/health-fitness/vivosmart-hr/prod531166.html (Accessed November 11, 2015).

Giles, D., Draper, N., and Neil, W. (2016). Validity of the Polar V800 heart rate monitor to measure RR intervals at rest. *Eur. J. Appl. Physiol.* 116, 563–571. doi: 10.1007/s00421-015-3303-9

Grant, S., Aitchison, T., Henderson, E., Christie, J., Zare, S., McMurray, J., et al. (1999). A comparison of the reproducibility and the sensitivity to change of visual analogue scales, Borg scales, and Likert scales in normal subjects during submaximal exercise. *Chest* 116, 1208–1217.

Halson, S. L. (2014a). Monitoring training load to understand fatigue in athletes. *Sports Med.* 44(Suppl. 2), S139–S147. doi: 10.1007/s40279-014-0253-z

Halson, S. L. (2014b). Sleep in elite athletes and nutritional interventions to enhance sleep. *Sports Med.* 44(Suppl. 1), S13–S23. doi: 10.1007/s40279-014-0147-0

Hargreaves, M. (2008). Physiological limits to exercise performance in the heat. *J. Sci. Med. Sport* 11, 66–71. doi: 10.1016/j.jsams.2007.07.002

Hausswirth, C., Louis, J., Aubry, A., Bonnet, G., Duffield, R., and LE Meur, Y. (2014). Evidence of disturbed sleep and increased illness in overreached endurance athletes. *Med. Sci. Sports Exerc.* 46, 1036–1045. doi: 10.1249/MSS.0000000000000177

Jawbone (2015). *UP3.* Retrieved from: https://jawbone.com/store/buy/up3 (Accessed October 22, 2015).

Jennings, D., Cormack, S., Coutts, A. J., Boyd, L., and Aughey, R. J. (2010). The validity and reliability of GPS units for measuring distance in team sport specific running patterns. *Int. J. Sports Physiol. Perform.* 5, 328–341.

Johnston, R. J., Watsford, M. L., Kelly, S. J., Pine, M. J., and Spurrs, R. W. (2014). Validity and interunit reliability of 10 Hz and 15 Hz GPS units for assessing athlete movement demands. *J. Strength Cond. Res.* 28, 1649–1655. doi: 10.1519/JSC.0000000000000323

Johnstone, J. A., Ford, P. A., Hughes, G., Watson, T., Mitchell, A. C., and Garrett, A. T. (2012). Field based reliability and validity of the bioharness multivariable monitoring device. *J. Sports Sci. Med.* 11, 643–652.

Kavanagh, J. J., and Menz, H. B. (2008). Accelerometry: a technique for quantifying movement patterns during walking. *Gait Posture* 28, 1–15. doi: 10.1016/j.gaitpost.2007.10.010

Lee, J. M., Kim, Y., and Welk, G. J. (2014). Validity of consumer-based physical activity monitors. *Med. Sci. Sports Exerc.* 46, 1840–1848. doi: 10.1249/MSS.0000000000000287

Leeder, J., Glaister, M., Pizzoferro, K., Dawson, J., and Pedlar, C. (2012). Sleep duration and quality in elite athletes measured using wristwatch actigraphy. *J. Sports Sci.* 30, 541–545. doi: 10.1080/02640414.2012.660188

LG Electronics (2015). *Lifeband Touch Activity Tracker.* Retrieved from: http://www.lg.com/us/mobile-accessories/lg-FB84-BL-activity-tracker (Accessed October 22, 2015).

Lumafit (2015). *Lumafit.* Retrieved from: http://www.lumafit.com/ (Accessed October 22, 2015).

Marino, M., Li, Y., Rueschman, M. N., Winkelman, J. W., Ellenbogen, J. M., Solet, J. M., et al. (2013). Measuring sleep: accuracy, sensitivity, and specificity of wrist actigraphy compared to polysomnography. *Sleep* 36, 1747–1755. doi: 10.5665/sleep.3142

Maughan, R. J., Otani, H., and Watson, P. (2012). Influence of relative humidity on prolonged exercise capacity in a warm environment. *Eur. J. Appl. Physiol.* 112, 2313–2321. doi: 10.1007/s00421-011-2206-7

Mazzeo, R. S. (2008). Physiological responses to exercise at altitude: an update. *Sports Med.* 38, 1–8. doi: 10.2165/00007256-200838010-00001

Medisana, A. G. (2015). *ViFit Connect Activity Tracker*. Retrieved from: http://www.medisana.com/en/Sport/Activity-Tracker/ViFit-connect-Activity-Tracker-mag.html (Accessed October 22, 2015).

Microsoft (2015). *Microsoft Band.* Retrieved from: http://www.microsoft.com/microsoft-band/en-us (Accessed October 22, 2015).

Mio Global (2015). *Mio ALPHA 2.* Retrieved from: http://www.mioglobal.com/Mio-ALPHA-2-Heart-Rate-Sport-Watch/Product.aspx?ProductID=28 (Accessed October 22, 2015).

Misfit Wearables. *Shine*. Retrieved from: http://misfit.com/products/shine

Moehrle, M. (2008). Outdoor sports and skin cancer. *Clin. Dermatol.* 26, 12–15. doi: 10.1016/j.clindermatol.2007.10.001

Myontec Ltd. (2015). *MBody Bike & Run.* Retrieved from: http://www.myontec.com/products/ (Accessed October 22, 2015).

Nike Inc. (2015a). *Nike+ Sportband.* Retrieved from: https://secure-nikeplus.nike.com/plus/products/sport_band/ (Accessed October 22, 2015).

Nike Inc. (2015b). Nike+ Sportwatch GPS. Retrieved from: https://secure-nikeplus.nike.com/plus/products/sport_watch/ (Accessed October 22, 2015).

Pandian, P. S., Mohanavelu, K., Safeer, K. P., Kotresh, T. M., Shakunthala, D. T., Gopal, P., et al. (2008). Smart vest: wearable multi-parameter remote physiological monitoring system. *Med. Eng. Phys.* 30, 466–477. doi: 10.1016/j.medengphy.2007.05.014

Philips (2016). *Actiwatch Spectrum PRO Get the Actiwatch Advantage.* Retrieved from: http://www.actigraphy.com/devices/actiwatch/actiwatch-pro.html (Accessed February 25, 2016).

Plews, D. J., Laursen, P. B., Le Meur, Y., Hausswirth, C., Kilding, A. E., and Buchheit, M. (2014). Monitoring training with heart rate-variability: how much compliance is needed for valid assessment? *Int. J. Sports Physiol. Perform.* 9, 783–790. doi: 10.1123/IJSPP.2013-0455

Plews, D. J., Laursen, P. B., Stanley, J., Kilding, A. E., and Buchheit, M. (2013). Training adaptation and heart rate variability in elite endurance athletes: opening the door to effective monitoring. *Sports Med.* 43, 773–781. doi: 10.1007/s40279-013-0071-8

Polar Electro (2015). *V800.* Retrieved from: http://www.polar.com/au-en/products/maximize_performance/running_multisport/v800 (Accessed October 22, 2015).

Ralph Lauren Media LLC (2015). *The Polotech Shirt.* Available online at: http://www.ralphlauren.com/product/index.jsp?productId=69917696 (Retrieved October 22, 2015).

Sadeh, A. (2011). The role and validity of actigraphy in sleep medicine: an update. *Sleep Med. Rev.* 15, 259–267. doi: 10.1016/j.smrv.2010.10.001

Saw, A. E., Main, L. C., and Gastin, P. B. (2015). Monitoring athletes through self-report: factors influencing implementation. *J. Sports Sci. Med.* 14, 137–146.

Sawka, M. N., Burke, L. M., Eichner, E. R., Maughan, R. J., Montain, S. J., and Stachenfeld, N. S. (2007). American College of Sports Medicine position stand. Exercise and fluid replacement. *Med. Sci. Sports Exerc.* 39, 377–390. doi: 10.1249/mss.0b013e31802ca597

Schäfer, A., and Vagedes, J. (2013). How accurate is pulse rate variability as an estimate of heart rate variability? A review on studies comparing photoplethysmographic technology with an electrocardiogram. *Int. J. Cardiol.* 166, 15–29. doi: 10.1016/j.ijcard.2012.03.119

Schutz, Y., and Chambaz, A. (1997). Could a satellite-based navigation system (GPS) be used to assess the physical activity of individuals on earth? *Eur. J. Clin. Nutr.* 51, 338–339. doi: 10.1038/sj.ejcn.160040

Seraphim Sense Ltd. (2014). *Angel Sensor.* Retrieved from: http://www.angelsensor.com/ (Accessed October 22, 2015).

Siegler, J. C., Robergs, R. A., Faria, E. W., Wyatt, F. B., and McCarthy, J. (2007). Noninvasive profiling of exercise-induced hypoxemia in competitive cyclists. *Res. Sports Med.* 15, 61–66. doi: 10.1080/15438620601184364

Speedy, D. B., Noakes, T. D., and Schneider, C. (2001). Exercise-associated hyponatremia: a review. *Emerg. Med. (Fremantle).* 13, 17–27. doi: 10.1046/j.1442-2026.2001.00173.x

Spierer, D. K., Rosen, Z., Litman, L. L., and Fujii, K. (2015). Validation of photoplethysmography as a method to detect heart rate during rest and exercise. *J. Med. Eng. Technol.* 39, 264–271. doi: 10.3109/03091902.2015.1047536

Stoppa, M., and Chiolerio, A. (2014). Wearable electronics and smart textiles: a critical review. *Sensors (Basel)* 14, 11957–11992. doi: 10.3390/s140711957

Suunto (2015). *Suunto Ambit3 Peak Sapphire (HR).* Retrieved from: http://www.suunto.com/Products/sports-watches/Suunto-Ambit3-Peak/Suunto-Ambit3-Peak-Sapphire-HR/?categoryId=3 (Accessed October 22, 2015).

Tan, A. M., Fuss, F. K., Weizman, Y., and Troynikov, O. (2015). Development of a smart insole for medical and sports purposes. *Procedia Eng.* 112, 152–156. doi: 10.1016/j.proeng.2015.07.191

Thompson, W. R. (2014). Worldwide survey of fitness trends for 2015: what's driving the market. *ACSM Health Fitness J.* 18, 8–17. doi: 10.1249/FIT.0000000000000073

Thompson, W. R. (2015). Worldwide survey of fitness trends for 2016: 10th anniversary edition. *ACSM Health Fitness J.* 19, 9–18. doi: 10.1249/FIT.0000000000000164

Varley, M. C., Fairweather, I. H., and Aughey, R. J. (2012). Validity and reliability of GPS for measuring instantaneous velocity during acceleration, deceleration, and constant motion. *J. Sports Sci.* 30, 121–127. doi: 10.1080/02640414.2011.627941

Villar, R., Beltrame, T., and Hughson, R. L. (2015). Validation of the Hexoskin wearable vest during lying, sitting, standing, and walking activities. *Appl. Physiol. Nutr. Metab.* 40, 1019–1024. doi: 10.1139/apnm-2015-0140

Virtanen, J., Noponen, T., Kotilahti, K., and Ilmoniemi, R. J. (2011). Accelerometer-based method for correcting signal baseline changes caused by motion artifacts in medical near-infrared spectroscopy. *J. Biomed. Opt.* 16:087005. doi: 10.1117/1.3606576

Windsor, J. S., and Rodway, G. W. (2014). Con: pulse oximetry is useful in predicting acute mountain sickness. *High Alt. Med. Biol.* 15, 442–443. doi: 10.1089/ham.2013.1140

Withings, S. A. (2015). *Pulse Ox.* Retrieved from: http://www.withings.com/eu/en/store/details/pulse-O2 (Accessed October 22, 2015).

Yang, C. C., and Hsu, Y. L. (2010). A review of accelerometry-based wearable motion detectors for physical activity monitoring. *Sensors (Basel)* 10, 7772–7788. doi: 10.3390/s100807772

Yang, S., and Li, Q. (2012). Inertial sensor-based methods in walking speed estimation: a systematic review. *Sensors (Basel)* 12, 6102–6116. doi: 10.3390/s120506102

Zephyr Technology Corp (2015). *BioHarness^{TM} 3.* Retrieved from: http://www.zephyranywhere.com/products/bioharness-3

Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Viewpoint

Recommendations for Assessment of the Reliability, Sensitivity, and Validity of Data Provided by Wearable Sensors Designed for Monitoring Physical Activity

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Abstract

Although it is becoming increasingly popular to monitor parameters related to training, recovery, and health with wearable sensor technology (wearables), scientific evaluation of the reliability, sensitivity, and validity of such data is limited and, where available, has involved a wide variety of approaches. To improve the trustworthiness of data collected by wearables and facilitate comparisons, we have outlined recommendations for standardized evaluation. We discuss the wearable devices themselves, as well as experimental and statistical considerations. Adherence to these recommendations should be beneficial not only for the individual, but also for regulatory organizations and insurance companies.

(JMIR Mhealth Uhealth 2018;6(4):e102) doi:10.2196/mhealth.9341

KEYWORDS

activity tracker; data mining; Internet of Things; load management; physical activity; smartwatch

Introduction

Wearable sensors (so-called “wearables”) are currently the world’s leading trend in fitness [1,2] and are being employed widely by various groups to monitor variables related to health, physical activity, training load, and recovery [3,4], often with the goal of individualizing physical activity and improving performance. Several insurance companies promote such monitoring [5] and an increasing number of organizations that regulate sports (eg, the International Football Association Board [6]), allow wearables to be worn during competitions (albeit with certain limitations).

If wearables are to be of value in enhancing health and performance [4], it is becoming more and more imperative that the data they supply are proven to be trustworthy by employing scientific approaches [7]. Unfortunately, wearables are often marketed with aggressive and exaggerated claims that lack a sound scientific basis [7], and the unreliable data they provide (and/or interpretation thereof) has resulted in costly class-action lawsuits [8] and provides little or no value to the customer.

Recent scientific evaluation of wearable data has involved widely heterogeneous study designs (including the nature and size of the study population), methodologies, criteria for comparisons, terminologies, and statistical analyses, as well as varying intensities/modalities of exercise. Assessment of novel technology may be influenced by the particular test conditions employed [9]. For example, laboratory data may not be transferable to real-life situations and data trustworthy in a resting condition or during low-intensity exercise may become less valid at higher intensity (eg, due to motion artifacts). Thus, variations in methodology complicate the comparison of scientific evaluations of wearable data.

From our perspective, athletes, manufacturers of wearables, and organizations concerned with health, sports, and insurance could all benefit from basic recommendations for assessment of the reliability, sensitivity, and validity of data provided by wearable sensors. The aim of this paper is to formulate such recommendations.

Factors Inherent to the Wearables Themselves

Sensor Characteristics

Wearables contain a wide variety of sensors (eg, electrochemical, optical, acoustic, and/or pressure-sensitive), as well as inertial measurement units and global navigation satellite systems (including global positioning systems [GPS]). More than one of these are often present within the same device. These sensors, produced by various manufacturers, are designed to monitor a variety of internal (eg, heart rate, tissue oxygenation, distribution of plantar pressure) and/or external (eg, acceleration of body segments, speed while exercising) parameters, mostly noninvasively [3]. With multi-sensor devices, the quality of data and parameters derived depends on the interplay between the sensors, each of which must therefore be scrutinized both independently and in combination with the others. Consideration of individual sensors is beyond the scope of the present recommendations and we refer the reader to other relevant work for such information [3,10,11].

Software

The nature of the software in the wearable itself, as well as of the software in any accompanying device (ie, laptop, smartphone application) exerts a considerable influence on data quality. For example, the software in GPS receivers or analytical software on an accompanying device may actually alter data [12-14]. We therefore urge researchers to describe the software utilized by the wearable and accompanying devices and/or the involvement of “cloud” technology in detail.

Acquisition of Raw Data: Sampling Frequency and Filtering

Although of less concern to the private consumer, to improve the reliability, sensitivity, and validity of data used for research purposes we recommend that manufacturers provide access to raw data. This issue is of particular interest in the case of multi-sensor devices, which often calculate a single value by combining data from several sensors (a common example being calculation of energy expenditure by merging heart rate with several GPS parameters), yet the contribution by each individual sensor is often unclear. Describing these contributions could enhance scientific trustworthiness (eg, by improving the algorithms employed).

A high sampling frequency, which normally enhances data quality, may be achieved artificially by filtering techniques (eg, interpolation) that produce no actual improvement in this quality [15]. Consequently, both the sampling frequency and any filtering techniques applied should be described in detail.

Durability

Sensors can deteriorate or even wear out with extended use and it is clearly important to describe the durability of the wearable and its sensor technology, at least as indicated by the manufacturer. Unlike laboratory equipment, most wearables are not checked routinely, making such description essential. Wearable devices are typically brand-new when evaluated and the quality and trustworthiness of the data they provide may change with use.

Precise Reporting of Anatomical Positioning

Wearables and their algorithms are often designed for use at a specific position or region of the body, which, consequently, must be indicated clearly. In certain cases, imprecise positioning may attenuate data quality [3]. For example, sensors for surface electromyography incorporated into clothing must be positioned precisely on the muscle, preferably along the midline, halfway between the entrance of the nerve and myotendinous junction [16]. On a daily basis, such accurate positioning may prove difficult, especially since this is often performed by nonprofessionals. Moreover, signal reproducibility may be affected by repeated donning and removal of garments. Consequently, we encourage researchers to describe in detail the positioning of wearables, as well as reproducibility of data. Researchers often evaluate several wearables simultaneously and such devices in close proximity can interfere with one another [15]. We recommend strongly that any potential interference be controlled for.

Experimental Considerations

Study Population

Selection of the study population (eg, cyclists, runners or team members, elite or recreational athletes, youth or adults, men or women) should accurately reflect the intended use of the wearable. Each population behaves differently (eg, with respect to lifestyle) and algorithms should be transferred from one specific population to another only with great care. The inclusion and exclusion criteria for participants must be described clearly. If anyone opts out of the experimental procedure or data analysis, a reason should be given.

Exercise Protocol

The intended purpose and conditions for use of the wearable should be clarified. If designed for monitoring general activity, data should be collected in connection with various forms of exercise (eg, running, cycling, rowing, intermittent activities, activities of daily living) of varying intensity (eg, resting, submaximal, high), in different positions (lying, sitting, or standing), and/or while moving freely. If a wearable is intended to be used in connection with team sports such as soccer, a protocol mimicking the demands of this sport–including low-speed running, straight sprints, change-of-direction, and tackling–is much more preferable than running constantly at low speed only.

Potential Confounders

Factors that could influence the outcome, such as temperature and humidity, the warm-up procedure, nutritional status, and any form of encouragement, should resemble the real-life situation as closely as possible [17,18] and be described in detail.

Other potential confounders may also need to be taken into consideration. For example, sensors that monitor electrical signals (eg, for electromyography or electrocardiography) may be influenced by other devices, such as a participant's pacemaker. Optical sensors (eg, for photoplethysmography) can be affected by the photosensitivity of the skin or by vasoconstriction [19,20]. In the case of GPS receivers, the horizontal dilution of precision, as well as the number of satellites to which the wearable is connected, should be reported [15]. Although there are no clear rules, two wearables should not be tested at the same time (eg, one on top of the other) or, if they are, potential interference and crosstalk should be examined for by switching the positions of the devices [21]. Adequate controlling for numerous confounding factors requires a good understanding of both the sensor technology and associated physiological and/or biomechanical processes.

Special Considerations Concerning Reliability

Intradevice reliability concerns reproducibility within the same device [22,23], while interdevice reliability (reproducibility with different devices) is to be tested if the devices in question are intended for interchangeable use [12]. Both types of reliability should be confirmed routinely. Recently, it has been recommended that at least 50 participants and three trials should be involved in order to obtain precise estimates of reliability [23]. When multiple trials are performed at different times, potential confounders must vary as little as possible.

Special Considerations Concerning Validity

Several different types of validity (eg, logical, convergent, and construct validity [24,25]) are probably equally important in this context, but discussion of these in detail is beyond the present scope and we refer the interested reader to other relevant articles [24,25]. Here, we focus on concurrent criterion validity, since this is probably easiest to access with respect to wearables. Concurrent criterion validity evaluates the association between data provided by the new device and another device considered to be more valid (sometimes referred to as a criterion measure or "gold-standard") [23,25].

For certain parameters, there are generally-accepted criterion measures (eg, polysomnographic parameters of sleep [26] and an ingestible telemetric sensor for core body temperature [27]). However, for others (eg, energy expenditure at several timepoints while moving freely and in-shoe plantar pressure) no such measures are currently available. We encourage researchers to describe the trustworthiness of their criterion measures and strongly discourage the use of measures not considered to be "gold-standard" for validation of the quality of wearable data.

Statistical Analyses

Overview

The various statistical approaches for evaluating the reliability or validity of wearables all have limitations [28,29]. Without discouraging the usage of other robust approaches (eg, the Standard Error of Measurement for reliability studies [28] or Bland-Altman plots for validity studies [30,31]), we propose one possible approach to statistical assessment of wearable data concerning reliability, sensitivity, and validity in the following sections.

Reliability

Reliability should be documented in terms of intrasubject variability (eg, measured as standard deviation, "...the random variation in a measure when one individual is tested many times"), which is possibly the most important indicator of the reliability of measures of performance and sometimes referred to as typical error (TE) [23]. The TE can also be expressed as the coefficient of variation (%CV) [23] and we encourage the reporting of both.

Another measure of reliability (eg, "...the change in mean value between 2 trials...") assesses systematic bias in combination with random variations [23]. The random variation is simply a sampling error, which tends to be smaller with larger samples. Systematic bias can be due to learning by (and training of) subjects or effects related to fatigue, and consequently can often be minimized by familiarization trials or adequate rest between trials, respectively [23].

In addition, researchers should assess test-retest reliability with the intraclass correlation coefficient [32], which "represents how closely the values of one trial track the values of another as we move our attention from individual to individual" [23] or, in other words, the reliability "of the position or rank of individuals in the group relative to others" [28]. Moreover, to determine whether data provided by different wearables can be used interchangeably, it may be of interest to evaluate interdevice reliability, previously accomplished by calculating the %CV between the devices when worn simultaneously [12].

Sensitivity

Wearables designed to track changes in performance and/or parameters over time must, of course, be sensitive to such changes [33]. Even with a reliable test, the noise can be high enough to mask changes in parameters [33]. In the case of individual elite athletes, for whom certain fitness parameters are directly correlated with performance (eg, energy expenditure at a given running intensity; the lower, the less intense), the smallest worthwhile change (SWC) is 30% of the individual's typical variation in performance [34]. Where there is no clear relationship between parameters of fitness and performance (eg, strength and team sport performance), it has been proposed that the SWC be calculated (0.2 times the between-subject standard deviation, based on Cohen's effect size principle) and compared with the noise of the measuring device or test [33,34]. This noise can be expressed as the TE, which can be obtained from reliability studies, as described above. A TE less than, similar to, or higher than the SWC can be rated as "good," "OK," or "marginal," respectively [33]. When assessing sensitivity, similar and reliable experimental approaches are required.

Validity

Linear regression analysis can be employed to identify bias and provide an estimate of the TE in wearable data [29,35,36]. Furthermore, Pearson's product-moment correlation coefficient should be calculated [36] to compare the degree of association [33,37] between data obtained with the criterion measure and the wearable. However, a significant correlation does not definitively mean that these data do not differ and is not, therefore, on its own a sufficient indicator of validity [30].

Conclusions

Here, we have outlined general recommendations (summarized in Table 1) for the evaluation of the trustworthiness of monitoring training load, recovery, and health by wearables. We are well aware that with certain technologies, other methodological considerations may be of particular importance and that new approaches are emerging constantly. Although evaluation may not be possible or even desirable in every individual context, findings in one situation should be transferred to another only with great care and appropriate justification.

The market for wearables is growing exponentially and their scientific evaluation in a trustworthy manner needs to keep pace. The success of a wearable device depends on gaining the trust of the consumer, stakeholders, and policymakers alike (eg, by transparent reporting of standardized validation, ideally carried out by an independent research institution). We are convinced that these recommendations can aid manufacturers of wearables, athletes, coaches, team managers, insurance companies, and other stakeholders and policymakers alike in evaluating wearable sensor technologies and/or selecting appropriate devices.

Table 1. Checklist of important considerations associated with the evaluation of data provided by wearables.

Factor	Action/recommendation
Sensor characteristics	• Scrutiny of each sensor
Software	• Specify calculations/algorithms • Report the version of software and firmware involved
Raw data	• Report sampling frequency • Report filtering techniques and aggregation
Durability	• Report the durability and age of the device
Anatomical positioning	• Report the precise anatomical positioning of sensors • Report signal reproducibility upon repeated putting on and taking off • Report considerations concerning positioning • Control for and describe potential interference
Study population	• Describe the target population • Specify inclusion and exclusion criteria • Generalize to other populations only with great care
Exercise protocol	• Describe conditions (eg, ambient temperature, altitude) in as much detail as possible • Investigate different forms of exercise (running, cycling, walking, moving freely) • Apply different intensities (lying, sitting, low and high intensity)
Confounders	• Report any potential confounding factors • Perform assessment in both controlled and real-life scenarios • Check for potential crosstalk between devices
Assessment of reliability	• Determine intradevice and interdevice reliability • Document intrasubject standard deviation • Report the coefficient of variation • Calculate the intraclass correlation coefficient • Recruit at least 50 participants • Report systematic bias
Assessment of sensitivity	• Calculate the smallest worthwhile change
Assessment of validity	• Choose an appropriate criterion measure and assess the reliability of this measure as well • Perform linear regression analysis • Calculate Pearson's product-moment correlation

Acknowledgments

This publication was funded by the German Research Foundation (DFG) and the University of Wuerzburg through the Open Access Publishing funding program.

Conflicts of Interest

None declared.

References

1. Thompson WR. Worldwide survey of fitness trends for 2017. ACSM Health Fitness J 2016;20(6):8-17. [doi: 10.1249/FIT.0000000000000252]
2. Thompson WR. Worldwide survey of fitness trends for 2016: 10th anniversary edition. ACSM Health Fitness J 2015;19(6):9-18. [doi: 10.1249/FIT.0000000000000164]
3. Düking P, Hotho A, Holmberg H, Fuss FK, Sperlich B. Comparison of non-invasive individual monitoring of the training and health of athletes with commercially available wearable technologies. Front Physiol 2016;7:71 [FREE Full text] [doi: 10.3389/fphys.2016.00071] [Medline: 27014077]
4. Düking P, Holmberg H, Sperlich B. Instant biofeedback provided by wearable sensor technology can help to optimize exercise and prevent injury and overuse. Front Physiol 2017 Apr;8:167 [FREE Full text] [doi: 10.3389/fphys.2017.00167] [Medline: 28420998]
5. Baas J. Die Techniker. 2016 Dec 22. Digitalisierung nutzen, um Gesundheit und die Solidargemeinschaft zu fördern URL: https://www.tk.de/tk/themen/digitale-gesundheit/gesundheitsfoederung-durch-fitnesstracker-interview-dr-jens-baas/931248 [accessed 2018-04-04] [WebCite Cache ID 6yQE4yKX4]
6. Brud L. The International Football Association Board. 2015 May. Amendments to the laws of the game - 2015/2016 and information on the completed reform of The International Football Association Board URL: http://resources.fifa.com/mm/document/affederation/ifab/02/60/91/38/circular_log_amendments_2015_v1.0_en_neutral.pdf [accessed 2017-02-19] [WebCite Cache ID 6yQEWMtkL]
7. Sperlich B, Holmberg H. Wearable, yes, but able…?: it is time for evidence-based marketing claims!. Br J Sports Med 2016 Dec 16 [FREE Full text] [doi: 10.1136/bjsports-2016-097295] [Medline: 27986762]
8. Eadicicco L. Time. 2016 May 23. 4 things to know about the Fitbit accuracy lawsuit URL: http://time.com/4344675/fitbit-lawsuit-heart-rate-accuracy/ [accessed 2018-04-04] [WebCite Cache ID 6yQIfOxnF]
9. Bassett DR, Rowlands A, Trost SG. Calibration and validation of wearable monitors. Med Sci Sports Exerc 2012 Jan;44(1 Suppl 1):S32-S38 [FREE Full text] [doi: 10.1249/MSS.0b013e3182399cf7] [Medline: 22157772]
10. Bandodkar AJ, Wang J. Non-invasive wearable electrochemical sensors: a review. Trends Biotechnol 2014 Jul;32(7):363-371. [doi: 10.1016/j.tibtech.2014.04.005] [Medline: 24853270]
11. Tiwana MI, Redmond SJ, Lovell NH. A review of tactile sensing technologies with applications in biomedical engineering. Sensor Actuat A-Phys 2012 Jun;179(1):17-31. [doi: 10.1016/j.sna.2012.02.051]
12. Buchheit M, Al HH, Simpson BM, Palazzi D, Bourdon PC, Di Salvo V, et al. Monitoring accelerations with GPS in football: time to slow down? Int J Sports Physiol Perform 2014 May;9(3):442-445. [doi: 10.1123/ijspp.2013-0187] [Medline: 23916989]
13. Roe G, Darrall-Jones J, Black C, Shaw W, Till K, Jones B. Validity of 10-HZ GPS and timing gates for assessing maximum velocity in professional rugby union players. Int J Sports Physiol Perform 2017 Jul;12(6):836-839. [doi: 10.1123/ijspp.2016-0256] [Medline: 27736256]
14. Lee J, Kim Y, Bai Y, Gaesser GA, Welk GJ. Validation of the SenseWear mini armband in children during semi-structure activity settings. J Sci Med Sport 2016 Jan;19(1):41-45. [doi: 10.1016/j.jsams.2014.10.004] [Medline: 25459233]
15. Malone JJ, Lovell R, Varley MC, Coutts AJ. Unpacking the black box: applications and considerations for using GPS devices in sport. Int J Sports Physiol Perform 2017 Apr;12(Suppl 2):S218-S226. [doi: 10.1123/ijspp.2016-0236] [Medline: 27736244]
16. De Luca CJ. The use of surface electromyography in biomechanics. J Appl Biomech 1997;13(2):135-163.
17. Halperin I, Pyne DB, Martin DT. Threats to internal validity in exercise science: a review of overlooked confounding variables. Int J Sports Physiol Perform 2015 Oct;10(7):823-829. [doi: 10.1123/ijspp.2014-0566] [Medline: 25756869]
18. Hopkins WG, Schabort EJ, Hawley JA. Reliability of power in physical performance tests. Sports Med 2001;31(3):211-234. [Medline: 11286357]
19. Spierer DK, Rosen Z, Litman LL, Fujii K. Validation of photoplethysmography as a method to detect heart rate during rest and exercise. J Med Eng Technol 2015;39(5):264-271. [doi: 10.3109/03091902.2015.1047536] [Medline: 26112379]
20. Chan ED, Chan MM, Chan MM. Pulse oximetry: understanding its basic principles facilitates appreciation of its limitations. Respir Med 2013 Jun;107(6):789-799 [FREE Full text] [doi: 10.1016/j.rmed.2013.02.004] [Medline: 23490227]
21. Weizman Y, Tan A, Fuss FK. Benchmarking study of smart-insole forces and centre of pressure. Submitted .
22. Atkinson G, Nevill AM. Statistical methods for assessing measurement error (reliability) in variables relevant to sports medicine. Sports Med 1998 Oct;26(4):217-238. [Medline: 9820922]

23. Hopkins WG. Measures of reliability in sports medicine and science. Sports Med 2000 Jul;30(1):1-15. [Medline: 10907753]
24. Tudor-Locke C, Williams JE, Reis JP, Pluto D. Utility of pedometers for assessing physical activity: convergent validity. Sports Med 2002;32(12):795-808. [Medline: 12238942]
25. Currell K, Jeukendrup AE. Validity, reliability and sensitivity of measures of sporting performance. Sports Med 2008;38(4):297-316. [Medline: 18348590]
26. Ancoli-Israel S, Cole R, Alessi C, Chambers M, Moorcroft W, Pollak CP. The role of actigraphy in the study of sleep and circadian rhythms. Sleep 2003 May 01;26(3):342-392. [Medline: 12749557]
27. Byrne C, Lim CL. The ingestible telemetric body core temperature sensor: a review of validity and exercise applications. Br J Sports Med 2007 Mar 01;41(3):126-133. [doi: 10.1136/bjsm.2006.026344]
28. Weir JP. Quantifying test-retest reliability using the intraclass correlation coefficient and the SEM. J Strength Cond Res 2005 Feb;19(1):231-240. [doi: 10.1519/15184.1] [Medline: 15705040]
29. Hopkins WG. Sport Science. 2004. Bias in Bland-Altman but not regression validity analyses URL: http://www.sportsci.org/jour/04/wghbias.htm [accessed 2018-04-04] [WebCite Cache ID 6yQIpBO2C]
30. Welk GJ, McClain J, Ainsworth BE. Protocols for evaluating equivalency of accelerometry-based activity monitors. Med Sci Sports Exerc 2012 Jan;44(1 Suppl 1):S39-S49. [doi: 10.1249/MSS.0b013e3182399d8f] [Medline: 22157773]
31. Bland JM, Altman DG. Measuring agreement in method comparison studies. Stat Methods Med Res 1999 Jun;8(2):135-160. [Medline: 10501650]
32. Shrout PE, Fleiss JL. Intraclass correlations: uses in assessing rater reliability. Psychol Bull 1979 Mar;86(2):420-428. [Medline: 18839484]
33. Buchheit M, Lefebvre B, Laursen PB, Ahmaidi S. Reliability, usefulness, and validity of the 30-15 Intermittent Ice Test in young elite ice hockey players. J Strength Cond Res 2011 May;25(5):1457-1464. [doi: 10.1519/JSC.0b013e3181d686b7] [Medline: 21522077]
34. Hopkins WG. Sport Science. 2004. How to interpret changes in an athletic performance test URL: http://www.sportsci.org/jour/04/wghtests.htm [accessed 2018-04-04] [WebCite Cache ID 6yQIFS8YY]
35. Hopkins WG, Marshall SW, Batterham AM, Hanin J. Progressive statistics for studies in sports medicine and exercise science. Med Sci Sports Exerc 2009 Jan;41(1):3-13. [doi: 10.1249/MSS.0b013e31818cb278] [Medline: 19092709]
36. Hopkins WG. Sport Science. 2010. A socratic dialogue on comparison of measures URL: http://www.sportsci.org/2010/wghmeasures.htm [accessed 2018-04-04] [WebCite Cache ID 6yQIP5eBC]
37. McCall A, Fanchini M, Coutts AJ. The modern-day sport-science and sports-medicine "quest for the holy grail". Int J Sports Physiol Perform 2017 May;12(5):704-706. [doi: 10.1123/ijspp.2017-0137] [Medline: 28488907]

Abbreviations

%CV: coefficient of variation
GPS: global positioning system
SWC: smallest worthwhile change
TE: typical error

Edited by G Eysenbach; submitted 06.11.17; peer-reviewed by L Ardigò, S Trost; comments to author 18.12.17; revised version received 08.02.18; accepted 17.02.18; published 30.04.18

Please cite as:
Düking P, Fuss FK, Holmberg HC, Sperlich B
Recommendations for Assessment of the Reliability, Sensitivity, and Validity of Data Provided by Wearable Sensors Designed for Monitoring Physical Activity
JMIR Mhealth Uhealth 2018;6(4):e102
URL: http://mhealth.jmir.org/2018/4/e102/
doi:10.2196/mhealth.9341
PMID:29712629

Original Paper

Wrist-worn Wearables for Monitoring Heart Rate and Energy Expenditure While Sitting or Performing Light-to-vigorous Physical Activity: Validation Study

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Abstract

Background: Physical activity reduces the incidences of noncommunicable diseases, obesity, and mortality, but a sedentary lifestyle is becoming increasingly common. Innovative approaches to monitor and promote physical activity are warranted. While individual monitoring of physical activity aids in the design of effective interventions to enhance physical activity, a basic prerequisite is that the monitoring devices exhibit high validity.

Objective: Our goal was to assess the validity of monitoring heart rate (HR) and energy expenditure (EE) while sitting or performing light-to-vigorous physical activity with 4 popular wrist-worn wearables (Apple Watch Series 4, Polar Vantage V, Garmin Fenix 5, and Fitbit Versa).

Methods: While wearing the 4 different wearables, 25 individuals performed 5 minutes each of sitting, walking, and running at different velocities (ie, 1.1 m/s, 1.9 m/s, 2.7 m/s, 3.6 m/s, and 4.1 m/s), as well as intermittent sprints. HR and EE were compared to common criterion measures: Polar-H7 chest belt for HR and indirect calorimetry for EE.

Results: While monitoring HR at different exercise intensities, the standardized typical errors of the estimates were 0.09-0.62, 0.13-0.88, 0.62-1.24, and 0.47-1.94 for the Apple Watch Series 4, Polar Vantage V, Garmin Fenix 5, and Fitbit Versa, respectively. Depending on exercise intensity, the corresponding coefficients of variation were 0.9%-4.3%, 2.2%-6.7%, 2.9%-9.2%, and 4.1%-19.1%, respectively, for the 4 wearables. While monitoring EE at different exercise intensities, the standardized typical errors of the estimates were 0.34-1.84, 0.32-1.33, 0.46-4.86, and 0.41-1.65 for the Apple Watch Series 4, Polar Vantage V, Garmin Fenix 5, and Fitbit Versa, respectively. Depending on exercise intensity, the corresponding coefficients of variation were 13.5%-27.1%, 16.3%-28.0%, 15.9%-34.5%, and 8.0%-32.3%, respectively.

Conclusions: The Apple Watch Series 4 provides the highest validity (ie, smallest error rates) when measuring HR while sitting or performing light-to-vigorous physical activity, followed by the Polar Vantage V, Garmin Fenix 5, and Fitbit Versa, in that order. The Apple Watch Series 4 and Polar Vantage V are suitable for valid HR measurements at the intensities tested, but HR data provided by the Garmin Fenix 5 and Fitbit Versa should be interpreted with caution due to higher error rates at certain intensities. None of the 4 wrist-worn wearables should be employed to monitor EE at the intensities and durations tested.

(JMIR Mhealth Uhealth 2020;8(4):e16716) doi: 10.2196/16716

KEYWORDS

cardiorespiratory fitness; innovation; smartwatch; technology; wearable; digital health

Introduction

Physical activity reduces the incidences of noncommunicable diseases, obesity, and mortality, but, unfortunately, according to the World Health Organization (WHO), a sedentary lifestyle is becoming increasingly common, with approximately 23% of the adult population failing to meet physical activity guidelines [1-3]. Accordingly, innovative approaches to promote and monitor physical activity are urgently warranted, as indicated in the WHO's global action plan [4]. While individual monitoring of physical activity aids in the design of effective interventions to enhance physical activity [5,6], a basic prerequisite is that the monitoring devices exhibit high validity.

Heart rate (HR) and energy expenditure (EE) are two key aspects of physical activity. HR reflects the intensity of physical activity [7,8], while monitoring EE is particularly helpful for individuals seeking to regulate their body mass or composition [9], since any imbalance between energy intake and EE may have negative consequences [10]. HR and EE vary widely between individuals, and careful monitoring is crucial to provide appropriate recommendations concerning physical activity and diet [10].

While several procedures for monitoring HR (eg, Holter monitors or chest belts) and EE (indirect calorimetry) are available, miniaturized sensors [11] potentially enable less restrictive monitoring. Utilization of data collected by miniaturized wearable sensors (wearables) to improve health and fitness is a current worldwide trend [12] that offers new opportunities for designing individualized interventions concerning physical activity [13]. Theoretically, wearables allow extensive monitoring of parameters related to physical activity over prolonged periods [14]. Rigorous validation of wearable sensors is paramount since insurance companies encourage and promote monitoring (with wearables representing a major component of this strategy) [15], the WHO aims to endorse digital health (including wearables) [16], and in Germany, state laws already permit physicians to prescribe digital health solutions [17].

Wearable manufacturers claim to enable noninvasive and accurate monitoring of HR and EE [18]. The market for wearables designed to improve health and fitness is growing rapidly, and companies release new versions of their technology at least once each year, with older versions disappearing from the market. Projections for wrist-worn wearables alone estimate that 152.7 million such devices will be shipped in 2019, with a compound annual growth rate of 6.2% until 2023 [19]. However, the validity of most commercially available wearables has not been assessed across a range of exercise intensities by independent research institutions [18,20,21]. Consequently, while the potential health benefits of wearables are considerable, their validity must first be assured.

Accordingly, the current investigation was designed to assess the validity of 4 commercially available**,** high-tech, and popular wearable models for monitoring HR and EE while sitting or performing light-to-vigorous physical exercise.

Methods

Our study protocol and data analysis were based on previous recommendations concerning the validation of the reliability of wearables for assessing parameters during physical activity [22].

Participants

After being informed about the experimental procedures, 25 healthy participants (11 men, 14 women; mean age 26 years, SD 7 years; mean body height 174 cm, SD 10 cm; mean body mass 70.1 kg, SD 12.0 kg) of Caucasian origin gave their written consent to participate. This study was performed in accordance with the Declaration of Helsinki and approved by our institute's ethical committee (Ethical approval number: EthikKomm-05/2019).

Experimental Procedures

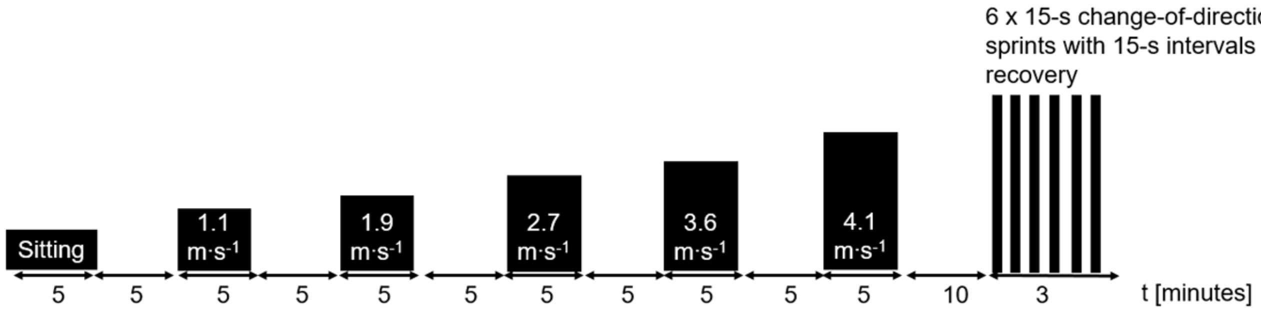
All participants visited the laboratory twice, with 3 days between visits, and tested 2 different wearables on each occasion. Environmental conditions were constant, with a temperature of 19.5 °C (SD 0.8 °C). Anthropometric data were collected during the first visit. Each wearable was attached to the wrist in the manner indicated by the manufacturer, and age, sex, height, and body mass were entered into the wearable's software, along with information about whether the wearable was on the left or right wrist.

The wearables and the order in which they were worn during the first and second visits were chosen in a random fashion, resulting in 25 measurements with each wearable.

Each participant was monitored while sitting as well as during walking and running at different speeds (1.1 m/s, 1.9 m/s, 2.7 m/s, 3.6 m/s, and 4.1 m/s) for 5 minutes, interspersed with 5 minutes of standing still. All participants also performed 6 ~30-m sprints involving multiple changes in direction (ranging from 10° to 180°) on the SpeedCourt (GlobalSpeed GmbH, Hemsbach, Germany) [23]. This involved sprinting between 12 contact plates installed symmetrically in a 5.25 m by 5.25 m square on the floor. A software program designed a path consisting of the 6 30-m sprints (approximately 15 seconds per 30-m sprint), with a display indicating the contact plates that had to be touched [23].

Figure 1 summarizes the sitting, walking, and running procedures.

Figure 1. Schematic illustration of the periods during which each participant was monitored (black bars).



Criterion Measures

A portable breath-by-breath gas analyzer (Metamax 3B, CORTEX Biophysik GmbH, Leipzig, Germany) employing standard algorithms for indirect calorimetry served as the criterion measure for EE. This system measures metabolic demands reliably [24] and has been used previously to assess the validity of wearables designed to monitor EE [25].

A Polar H7 chest belt, commonly employed for similar evaluations [26,27], was synchronized with the gas analyzer and served as the criterion measure for HR.

Wearables

The 4 tested wrist-worn wearables were Apple Watch Series 4, Version 5.1 (Apple Inc, Cupertino, CA); Polar Vantage V, Firmware 3.1.7 (Polar Electro Oy, Kempele, Finland); Garmin Fenix 5, Software 7.6 (Garmin, Olathe, KS); and Fitbit Versa, Version 32.33.1.30 (Fitbit Inc, San Francisco, CA).

All utilize photoplethysmography to monitor HR, but, to the best of our knowledge, information concerning the data used to calculate EE is not publicly available. Each wearable was positioned firmly, yet comfortably, on the wrist as in real life and as recommended by the manufacturers.

In the case of the Apple Watch Series 4, the “indoor walking” mode was selected for measurements while sitting or walking at 1.1 m/s; “running indoor” for speeds from 1.9 m/s to 4.1 m/s; and “HIIT” for the intermittent sprints. For the Polar Vantage V, the “Running (Treadmill)” mode was selected for all the monitoring periods, except for the intermittent sprints involving many and frequent changes in direction, for which “Soccer” was chosen. With the Garmin Fenix 5 and Fitbit Versa, the “Treadmill” mode was chosen for all monitoring periods.

All data were transmitted via Bluetooth and synchronized with the accompanying smartphone applications, in accordance with the manufacturers’ recommendations. For the Apple Watch Series 4, the raw data were exported to Microsoft Excel (Microsoft Corp, Redmond, WA) via the Apple Health App (Apple Inc, Cupertino, CA). In the cases of Polar, Garmin, and Fitbit, data were exported via specific buttons in the accompanying online software or collected directly from the software.

Statistical Analysis

Statistical analysis was performed in accordance with previous recommendations, whenever applicable [22]. Prior to analysis, the data were log-transformed to avoid bias resulting from nonuniformity of error. All data were analyzed in custom-designed Microsoft Excel spreadsheets [28]. For each exercise, the standardized mean bias was calculated. As recommended and carried out previously, linear regression was employed to analyze validity [22,29]. The standardized mean bias, standardized typical error of the estimate (sTEE), coefficient of variation (CV), and Pearson’s product-moment correlation coefficient are all reported.

The sTEE, based on half the thresholds of the modified Cohen’s scale, was employed to assess validity: <0.1, trivial; 0.1-0.29, small; 0.3-0.59, moderate; 0.6-1.0, large; 1.0-2.0, very large; >2.0, extremely large [28]. Pearson’s *r* was utilized to evaluate the correlation between the criterion measure and wearable as follows: 0.45-0.69, very poor; 0.70-0.84, poor; 0.85-0.94, good; 0.95-0.994, very good; ≥0.995, excellent [30]. The 90% confidence limits (coefficient of variation [CV]) for the statistical parameters are also reported. Absolute errors were calculated based on these CVs and the mean value obtained by the criterion measure.

The level of physical activity was defined in terms of the metabolic equivalent (MET), with <3 MET indicating light, <6 MET medium, and >6 MET vigorous physical activity [31]. To define physical activity levels, the EE provided by the criterion measure was extrapolated to 1 hour and divided by the mean body weight of the participant.

Results

Heart rate

The mean HR, CV, Pearson’s *r*, and sTEE with 90% confidence limits and interpretations are summarized in Table 1.

Table 1. Analysis of the validity of heart rate measurements by wrist-worn wearables while sitting or walking/running at different intensities.

Level of activity (METs[a]), intensity	Apple Watch Series 4	Polar Vantage V	Garmin Fenix 5	Fitbit Versa
Inactive (1.3), sitting				
Heart rate (bpm)[b], mean (SD)	68.8 (11.7)			
Standardized mean bias	0.03 (–0.02 to 0.07)	–0.06 (–0.11 to –0.02)	0.12 (–0.07 to 0.31)	–0.06 (–0.27 to 0.15)
Pearson's *r*	0.99 (0.99-1)	0.99 (0.98-1)	0.89 (0.77-0.95)	0.91 (0.77-0.96)
Interpretation of Pearson's *r*	Excellent	Excellent	Good	Good
CV[c] (%)	2 (1.6-2.6)	2.2 (1.8-2.9)	7.7 (6.1-10.7)	8 (6.1-12.1)
sTEE[d]	0.12 (0.09-0.17)	0.13 (0.10-0.19)	0.63 (0.41-1.03)	0.47 (0.28-0.82)
Interpretation of sTEE	Small	Small	Large	Moderate
Light (3.5), 1.1 m/s				
Heart rate (bpm)[b], mean (SD)	95.8 (25.0)			
Standardized mean bias	0.01 (–0.07 to 0.09)	–0.07 (–0.32 to 0.17)	0.12 (–0.10 to 0.34)	–0.28 (–7.00 to 0.13)
Pearson's *r*	0.97 (0.95-0.99)	0.89 (0.79-0.94)	0.85 (0.70-0.93)	0.57 (0.31-0.70)
Interpretation of Pearson's *r*	Very good	Good	Good	Very poor
CV (%)	2.9 (2.3-3.8)	5.5 (4.4-7.3)	5.8 (4.5-8.0)	9.6 (7.8-12.6)
sTEE	0.23 (0.16-0.34)	0.54 (0.37-0.82)	0.62 (0.40-1.03)	1.43 (0.87-3.03)
Interpretation of sTEE	Small	Moderate	Large	Very large
Vigorous (6.6), 1.9 m/s				
Heart rate (bpm)[b], mean (SD)	127 (19.4)			
Standardized mean bias	–0.02 (–0.10 to 0.06)	–0.34 (–0.53 to –0.16)	0.06 (–0.17 to 0.29)	–0.05 (–0.34 to 0.24)
Pearson's *r*	0.97 (0.95-0.99)	0.91 (0.82-0.95)	0.83 (0.65-0.92)	0.54 (0.29-0.71)
Interpretation of Pearson's *r*	Very good	Good	Poor	Very poor
CV (%)	2.9 (2.3-3.8)	5.4 (4.3-7.2)	9.2 (7.2-12.9)	19.1 (15.7-24.7)
sTEE	0.23 (0.16-0.34)	0.46 (0.32-0.69)	0.68 (0.43-1.16)	1.58 (0.98-3.25)
Interpretation of sTEE	Small	Moderate	Large	Very large
Vigorous (9.9), 2.7 m/s				
Heart rate (bpm)[b], mean (SD)	167 (16.5)			
Standardized mean bias	–0.13 (–0.49 to 0.24)	–0.37 (–0.57 to –0.16)	–0.56 (–0.87 to –0.24)	–0.82 (–1.18 to –0.47)
Pearson's *r*	1 (0.99-1)	0.88 (0.78-0.94)	0.63 (0.34-0.81)	0.52 (0.27-0.70)
Interpretation of Pearson's *r*	Excellent	Good	Very poor	Very poor
CV (%)	0.9 (0.7-1.2)	5.9 (4.8-7.9)	8.3 (6.6-11.4)	8.5 (7.0-11.0)
sTEE	0.09 (0.06-0.12)	0.53 (0.36-0.81)	1.24 (0.74-2.73)	1.64 (1.01-3.59)
Interpretation of sTEE	Trivial	Moderate	Very large	Very large
Vigorous (10.4), 3.6 m/s				
Heart rate (bpm)[b], mean (SD)	170 (15.3)			
Standardized mean bias	0.02 (–0.09 to 0.14)	–0.75 (–1.05 to –0.46)	–0.40 (–0.60 to –0.19)	–1.17 (–1.47 to –0.87)
Pearson's *r*	0.94 (0.89-0.97)	0.86 (0.74-0.93)	0.82 (0.67-0.91)	0.82 (0.67-0.91)
Interpretation of Pearson's *r*	Good	Good	Poor	Poor
CV (%)	3.0 (2.4-4.0)	4.9 (3.9-6.5)	8.9 (7.19-12.1)	4.1 (3.3-5.5)
sTEE	0.35 (0.24-0.51)	0.59 (0.40-0.91)	0.69 (0.46-1.11)	0.70 (0.47-1.11)
Interpretation of sTEE	Moderate	Moderate	Large	Large

Level of activity (METs[a]), intensity	Apple Watch Series 4	Polar Vantage V	Garmin Fenix 5	Fitbit Versa
Vigorous (13.3), 4.1 m/s				
Heart rate (bpm)[b], mean (SD)	177 (8.5)			
Standardized mean bias	–0.27 (–0.51 to –0.03)	–0.72 (–0.95 to –0.49)	–1.47 (–1.88 to –1.06)	–2.06 (–3.17 to –0.95)
Pearson's *r*	0.85 (0.71-0.93)	0.89 (0.76-0.95)	0.82 (0.65-0.91)	0.68 (0.24-0.89)
Interpretation of Pearson's *r*	Good	Good	Poor	Very poor
CV (%)	4.3 (3.4-5.8)	3.9 (3.0-5.6)	2.88 (2.28-3.96)	3.22 (2.34-5.35)
sTEE	0.62 (0.41-1.00)	0.50 (0.31-0.84)	0.69 (0.44-1.17)	1.09 (0.52-4.13)
Interpretation of sTEE	Large	Moderate	Large	Very large
Vigorous (13.8), intermittent sprints				
Heart rate (bpm)[b], mean (SD)	153 (14.7)			
Standardized mean bias	0.12 (0.03 to 0.21)	–0.99 (–1.54 to –0.44)	–1.75 (–2.28 to –1.21)	–2.01 (–2.58 to –1.43)
Pearson's *r*	0.92 (0.85-0.96)	0.75 (0.53-0.88)	0.58 (0.28-0.78)	0.53 (0.15-0.77)
Interpretation of Pearson's *r*	Good	Poor	Very poor	Very poor
CV (%)	3.5 (2.8-4.7)	6.7 (5.3-9.3)	8.4 (6.6-11.6)	9.0 (6.9-13.4)
sTEE	0.38 (0.25-0.64)	0.88 (0.54-1.73)	1.44 (0.80-5.40)	1.94 (0.84-5.25)
Interpretation of sTEE	Moderate	Large	Very large	Very large
Vigorous (8.8), average of the values at all different intensities				
Heart rate (bpm)[b], mean	137			
Standardized mean bias	0.03	–0.47	–0.55	–0.92
Pearson's *r*	0.95	0.88	0.77	0.65
Interpretation of Pearson's *r*	Very good	Good	Poor	Very poor
CV (%)	2.79	4.93	7.30	8.79
sTEE	0.29	0.52	0.86	1.26
Interpretation of sTEE	Moderate	Moderate	Large	Very large

[a]METs: metabolic equivalents.

[b]Measured according to the criterion measure.

[c]CV: coefficient of variation.

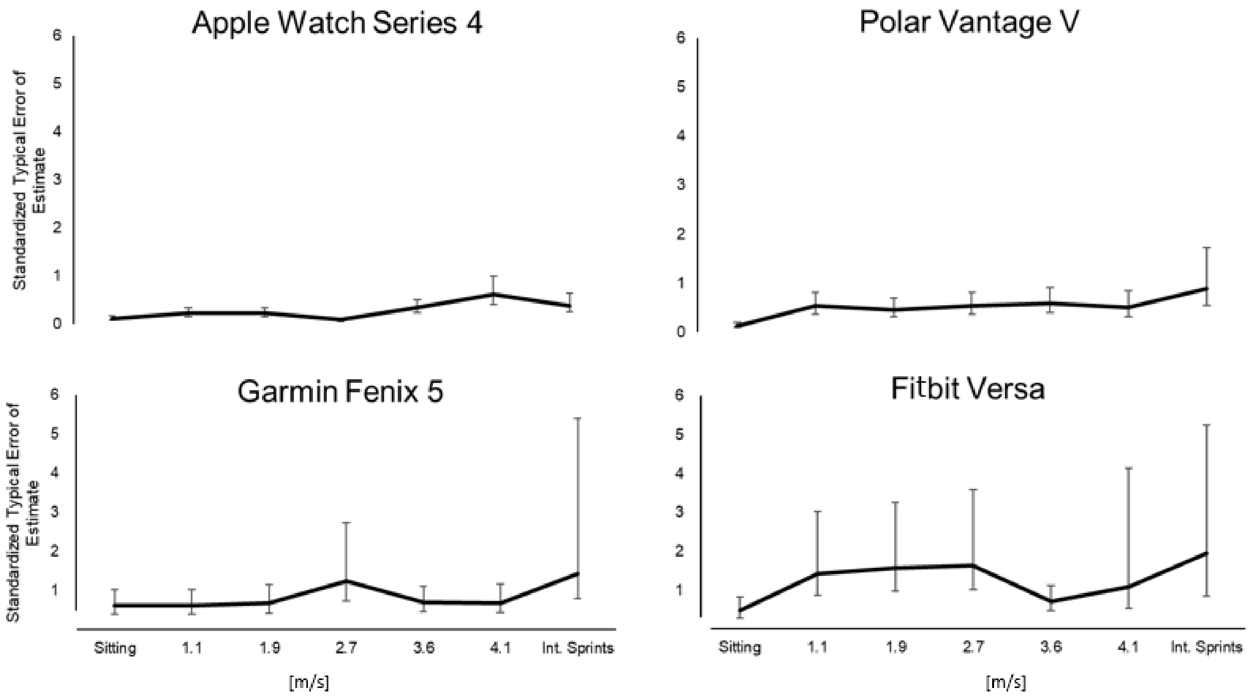
[d]sTEE: standardized typical error of the estimate.

Figure 2 documents the sTEE for the HR values provided by the wearables at all exercise intensities.

For HR monitoring at the different intensities, the sTEE was 0.09-0.62, 0.13-0.88, 0.62-1.24, and 0.47-1.94 for the Apple Watch Series 4, Polar Vantage V, Garmin Fenix 5, and Fitbit Versa, respectively, with corresponding CVs of 0.9%-4.3%, 2.2%-6.7%, 2.88%-9.2%, and 4.1%-19.1%, respectively. The sTEE was less affected by intensity in the case of the Apple Watch Series 4 and Polar Vantage V devices than with the Garmin Fenix 5 and Fitbit Versa devices.

sTEE and CV peaked during the intermittent sprints for all the wearables except the Apple Watch Series 4.

Figure 2. Standardized typical errors of the estimate (90% CI) for heart rate monitoring by the wearables while sitting or performing light-to-vigorous physical activity.



Energy Expenditure

The mean EE, CV, Pearson’s correlation coefficient, and sTEE with 90% confidence limits and interpretations are shown in Table 2.

Figure 3 depicts the sTEE for the EE values provided by all 4 wearables during exercise at different intensities.

These sTEE values were 0.34-1.84, 0.32-1.33, 0.46-4.86, and 0.41-1.65 for the Apple Watch Series 4, Polar Vantage V, Garmin Fenix 5, and Fitbit Versa, respectively, with corresponding CVs of 13.5%-27.1%, 16.3%-28.0%, 15.9%-34.5%, and 8.0%-32.3%, respectively.

Table 2. Analysis of the validity of energy expenditure measurements by wrist-worn wearables while sitting and walking/running at different intensities.

Level of activity (METs[a]), intensity	Apple Watch Series 4	Polar Vantage V	Garmin Fenix 5	Fitbit Versa
Inactive (1.3), sitting				
Energy expenditure (kcal/5 min)[b], mean (SD)	7.6 (1.6)			
Standardized mean bias	2.59 (2.25 to 2.94)	0.25 (–0.40 to 0.90)	1.74 (0.77 to 2.71)	–0.72 (–1.46 to 0.02)
Pearson's *r*	0.46 (0.16 to 0.68)	0.41 (0.10 to 0.65)	0.23 (–0.15 to 0.55)	0.52 (0.16 to 0.76)
Interpretation of Pearson's *r*	Very poor	-	•	Very poor
CV[c] (%)	26.6 (21.2-36.2)	28.0 (22.2-38.4)	20.9 (16.3-29.7)	17.1 (13.2-24.7)
sTEE[d]	1.84 (1.02-5.64)	1.33 (0.79-2.94)	4.24 (1.51-6.46)	1.65 (0.87-6.09)
Interpretation of sTEE	Very large	Very large	Extremely large	Very large
Light (3.5), 1.1 m/s				
Energy expenditure (kcal/5 min)[b], mean (SD)	20.6 (4.1)			
Standardized mean bias	2.63 (2.23 to 2.03	1.29 (0.87 to 1.72)	–0.05 (–0.84 to 0.74)	4.16 (3.97 to 4.36)
Pearson's *r*	0.71 (0.49 to 0.85)	0.67 (0.44 to 0.82)	0.20 (–0.19 to 0.54)	0.88 (0.76 to 0.94)
Interpretation of Pearson's *r*	Poor	Very poor	-	Good
CV (%)	15.1 (12.0-20.5)	16.3 (13.1-22.1)	16.8 (13.1-24.0)	8.0 (6.3-11.2)
sTEE	0.99 (0.63-1.77)	1.10 (0.70-2.03)	4.86 (1.56-5.11)	0.53 (0.35-0.85)
Interpretation of sTEE	Large	Very large	Extremely large	Moderate
Vigorous (6.6), 1.9 m/s				
Energy expenditure (kcal/5 min)[b], mean (SD)	38.3 (6.5)			
Standardized mean bias	1.58 (1.27 to 1.90)	0.27 (–0.18 to 0.71)	–1.15 (–2.01 to –0.29)	0.88 (0.56 to 1.20)
Pearson's *r*	0.71 (0.49 to 0.84)	0.49 (0.18 to 0.7)	0.21 (–0.21 to 0.56)	0.78 (0.57 to 0.89)
Interpretation of Pearson's *r*	Poor	Very poor	•	Poor
CV (%)	13.5 (10.8-18.1)	17.1 (13.7-23.1)	15.9 (12.2-23.3)	11.2 (8.8-15.7)
sTEE	0.99 (0.64-1.76)	0.65 (0.43-1.02)	4.62 (1.46-4.73)	0.81 (0.51-1.44)
Interpretation of sTEE	Large	Large	Extremely large	Large
Vigorous (9.9), 2.7 m/s				
Energy expenditure (kcal/5 min)[b], mean (SD)	57.8 (11.0)			
Standardized mean bias	0.79 (0.56 to 1.02)	–0.09 (–0.39 to 0.2)	–0.04 (–0.45 to 0.37)	–0.06 (–0.44 to 0.32)
Pearson's *r*	0.80 (0.62 to 0.90)	0.72 (0.51 to 0.85)	0.57 (0.25 to 0.78)	0.74 (0.51 to 0.87)
Interpretation of Pearson's *r*	Poor	Poor	Very poor	Poor
CV (%)	19.0 (15.1-26.2)	21.9 (17.5-29.8)	17.1 (13.3-24.4)	14.1 (11-19.8)
sTEE	0.76 (0.50-1.25)	0.97 (0.62-1.68)	1.43 (0.80-3.91)	0.90 (0.50-1.67)
Interpretation of sTEE	Large	Large	Very large	Large
Vigorous (10.4), 3.6 m/s				
Energy expenditure (kcal/5 min)[b], mean (SD)	60.5 (26.7)			
Standardized mean bias	0.32 (0.19 to 0.45)	–0.05 (–0.18 to 0.08)	0.19 (–0.10 to 0.48)	–0.06 (–0.37 to 0.24)
Pearson's *r*	0.95 (0.89 to 0.97)	0.95 (0.89 to 0.97)	0.84 (0.68 to 0.92)	0.76 (0.52 to 0.88)

Level of activity (METs[a]), intensity	Apple Watch Series 4	Polar Vantage V	Garmin Fenix 5	Fitbit Versa
Interpretation of Pearson's *r*	Very good	Very good	Poor	Poor
CV (%)	20.3 (16.0-28.3)	20.7 (16.4-28.6)	34.5 (26.4-50.8)	32.3 (24.6-48)
sTEE	0.34 (0.23-0.50)	0.34 (0.24-0.51)	0.64 (0.41-1.09)	0.87 (0.53-1.65)
Interpretation of sTEE	Moderate	Moderate	Large	Large
Vigorous (13.3), 4.1 m/s				
Energy expenditure (kcal/5 min)[b], mean (SD)	77.8 (46.6)			
Standardized mean bias	0.34 (0.13 to 0.54)	–0.11 (–0.28 to 0.05)	0.25 (–0.06 to 0.55)	0.13 (–0.09 to 0.34)
Pearson's *r*	0.93 (0.82 to 0.98)	0.95 (0.87 to 0.98)	0.91 (0.78 to 0.96)	0.92 (0.81 to 0.97)
Interpretation of Pearson's *r*	Good	Very good	Good	Good
CV (%)	27.1 (19.6-45.1)	22.7 (16.5-37.3)	33.1 (24.3-52.9)	29.9 (21.8-48.6)
sTEE	0.39 (0.23-0.71)	0.32 (0.19-0.57)	0.46 (0.28-0.80)	0.41 (0.24-0.72)
Interpretation of sTEE	Moderate	Moderate	Moderate	Moderate
Vigorous (13.8), intermittent sprints				
Energy expenditure (kcal/5 min)[b], mean (SD)	80.4 (15.6)			
Standardized mean bias	1.83 (1.52 to 2.13)	0.23 (0.04 to 0.42)	–0.82 (–1.78 to 0.14)	–1.25 (–1.83 to –0.67)
Pearson's *r*	0.66 (0.41 to 0.81)	0.85 (0.72 to 0.92)	0.21 (–0.19 to 0.56)	0.42 (0.06 to 0.68)
Interpretation of Pearson's *r*	Very poor	Good	-	-
CV (%)	25.4 (20.2-34.7)	17.5 (14.0-23.6)	17.9 (13.8-25.9)	20.8 (16.2-29.6)
sTEE	1.15 (0.72-2.19)	0.63 (0.43-0.97)	4.62 (1.50-5.05)	1.64 (0.88-5.57)
Interpretation of sTEE	Very large	Large	Extremely large	Very large
Vigorous (8.8), average of the values at all different intensities				
Energy expenditure (kcal/5 min)[b], mean	49.0			
Standardized mean bias	1.44	0.26	0.02	0.44
Pearson's *r*	0.75	0.72	0.45	0.72
Interpretation of Pearson's *r*	Poor	Poor	Very poor	Poor
CV (%)	21.0	20.6	22.3	19.1
sTEE	0.92	0.76	2.98	0.97
Interpretation of sTEE	Large	Large	Extremely large	Large

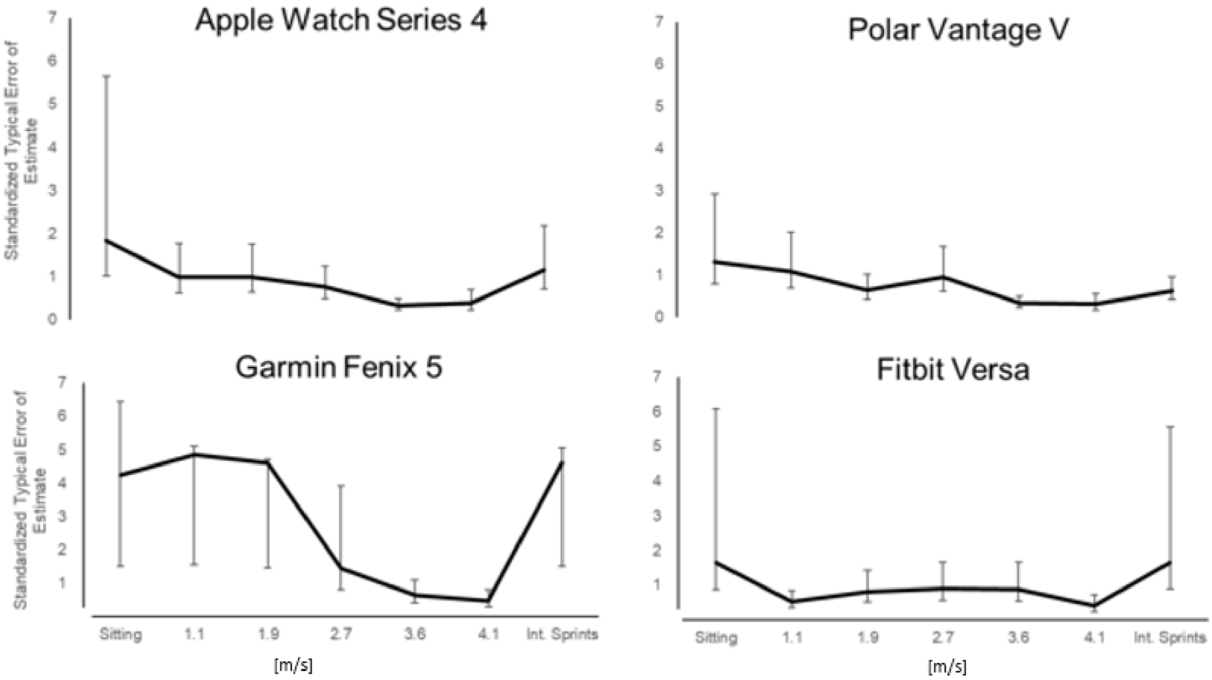
[a]METs: metabolic equivalents.

[b]Measured according to the criterion measure.

[c]CV: coefficient of variation.

[d]sTEE: standardized typical error of the estimate.

Figure 3. Standardized typical errors of the estimate (90% CI) for energy expenditure monitoring by the wearables while sitting or performing light-to-vigorous physical activity.



Discussion

The current investigation was designed to assess the validity of 4 commercially available wrist-worn wearables for monitoring HR and EE while sitting or performing light-to-vigorous physical activity.

The following paragraphs outline our major findings.

For monitoring HR during sitting or walking/running up to 2.7 m/s or with a HR up to 167 bpm, the Apple Watch Series 4 demonstrated the highest validity (average 2.3 bpm deviation from the criterion measure), followed by the Polar Vantage V (5.9 bpm), Garmin Fenix 5 (9.1 bpm), and Fitbit Versa (13.3 bpm).

For monitoring HR when running at 3.6 m/s or faster, performing intermittent sprints, or with a HR of 153-177 bpm, the Apple Watch Series 4 again exhibited the highest validity (average 6.0 bpm deviation from the criterion measure), followed by the Polar Vantage V (8.5 bpm), Fitbit Versa (8.8 bpm), and Garmin Fenix 5 (11.0 bpm).

Overall, when measuring HR, the Apple Watch Series 4 was the most valid (average 3.9 bpm deviation from the criterion measure), followed by the Polar Vantage V (7.0 bpm), Garmin Fenix 5 (9.9 bpm), and Fitbit Versa (11.4 bpm).

The validity of HR monitoring by the Apple Watch Series 4 and Polar Vantage V tended to be influenced less by the exercise intensity than that with the Garmin Fenix 5 and Fitbit Versa.

On average, all 4 wearables were poor at monitoring EE at the tested intensities and durations. The Apple Watch Series 4 deviated from the criterion measure by 124 kcal/h (CV 21%), Polar Vantage V by 121 kcal/h (CV 20%), Garmin Fenix 5 by 131 kcal/h (CV 22%), and Fitbit Versa by 112 kcal/h (CV 19%): average for the different intensities, with extrapolation of the CV for the 5-minute measurements to 1 hour.

To the best of our knowledge, this is the first assessment of the validity of these specific wrist-worn wearables. This is not surprising, since companies rarely rigorously validate new wearable models [20,21]. Comparison of our findings to earlier models requires caution, since it is not known whether the sensors or algorithms have been changed. However, such comparison might be of value to the manufacturers and to generally estimate if the parameters provided by the different manufacturers tend to be valid.

Heart Rate Measurement

Previous comparison of earlier models of wrist-worn wearables sold by Apple, Polar, Garmin, and Fitbit at different intensities concluded that the Apple Watch Series 2 demonstrated the best validity for monitoring HR during exercise, followed by the Polar A380, Fitbit Blaze, Fitbit Charge 2, and Garmin Vivosmart HR, in that order, with absolute mean percentage errors of 4.1%, 19.5%, 21.1%, 21.4%, and 25.4%, respectively [32].

Another earlier comparison of the error rates of the Apple Watch (version not indicated), Fitbit Charge HR, and Garmin Forerunner 225 during light and vigorous running on a treadmill found that the Apple Watch displayed the highest validity (mean absolute percentage error of 1.1%-6.7%), followed by the Fitbit Charge HR (2.4%-17.0%) and Garmin Forerunner 225 (7.8%-24.4%) [33].

In addition, Thomson et al [34] validated HR measurements from the Fitbit Charge HR2 and Apple Watch of 30 young adults performing the Bruce Protocol and concluded that the relative error rates of the latter (2.4%-5.1%) were lower than for the Fitbit wearable (3.9%-13.5%) at all the investigated exercise intensities.

Thus, these previous and our present findings indicate that the wrist-worn wearables made by Apple Inc and Polar Electro Oy exhibit the highest validity for measuring HR during physical activity at different levels, followed by Garmin or Fitbit wearables. However, additional comparative studies with different populations and different activities are required.

Consequently, based on these findings we recommend that researchers who wish to assess HR during different physical activities use the Apple Watch Series 4.

Energy Expenditure

The majority of the sTEE values for the EE values provided by all the wearables were large, very large, or extremely large. Even though the Apple Watch Series 4 had the best validity, its sTEE values ranged from moderate to very large, while those for the Polar Vantage V, Garmin Fenix 5, and Fitbit Versa ranged from moderate to extremely large, with no apparent dependency on exercise intensity. Since these error rates exceed acceptable levels of validity, we cannot determine whether the unpredictable arm movements associated with the intermittent multidirectional sprint protocol affected the validity.

Thus, utilization of these wearables by researchers monitoring EE during interventions designed to increase physical activity is likely to lead to flawed conclusions. They would not assist with enhancing physical activity or counteracting noncommunicable diseases and would instead endanger the trustworthiness of applying consumer grade wearables to improve health.

These findings of the poor validity of wrist-worn wearables for monitoring EE are in line with previous reports. Bai et al [35] found that the Apple Watch Series 1 had a smaller mean absolute percentage error (15.2%) when assessing EE than the Fitbit Wearable (32.9%), both when sedentary and during aerobic and light-to-vigorous physical activity [35].

Wahl et al [25] concluded that none of the 11 wrist-worn wearables they investigated, including devices from Garmin and Fitbit, should be used to monitor EE while performing activities of intensities similar to those investigated here. In a systematic review published in 2015, Evenson et al [21] stated that the validity of wearables for monitoring EE is low.

At the same time, when Kinnunen et al [36] aimed to assess the long-term validity of wrist-worn motion sensors for monitoring daily EE, they were able to explain as much as 85% of the variation in total EE (compared to the double-labelled water procedure) by including HR during weekly exercises in their analysis. This indicates the potential usefulness of wrist-worn wearables for estimating EE.

In a previous study that took age, gender, body mass, and HR into account, the correlation coefficient for predicting EE during 10 minutes of exercise could be as high as 0.913 with a mixed model [37]. Considering the considerable validity of HR measurements by wearables and the ability to incorporate all the information required into an appropriate algorithm, we believe that more precise estimation of EE by the wearables examined here should be feasible.

However, our findings and most of the available scientific literature indicate that the wearables investigated here should not be employed to estimate EE at these exercise intensities for the durations assessed. Here, we monitored EE for <5 minutes, since countries such as the United States or Australia promote such short periods of physical activity in their guidelines [38,39]. In this context, certain studies have demonstrated positive effects of even very brief vigorous exercise, such as walking up a staircase 3 times on 3 separate days each week for 6 weeks [40]. Whether these devices can be used to monitor EE reliably over longer time periods remains to be determined.

Our experiment involved Caucasians performing light-to-vigorous exercise on a treadmill under laboratory conditions, and extrapolation of our findings to other populations or settings (eg, cycling, rowing, strength training) must be performed with caution [22]. For example, skin color may influence assessment of HR by photoplethysmography. Moreover, since our participants performed either light or vigorous physical activity, we cannot draw conclusions about validity at moderate levels.

We wish to emphasize that our current findings only apply to the specific modes of the wearables we used (eg, the “indoor walking mode” for the Apple Watch) selected for the different physical activities and that other modes might give different results. The Apple Watch Series 4 and Polar Vantage V allow selection of more differentiated modes of activity (eg, the “indoor walking” and “indoor running” modes were selected on the Apple Watch for the corresponding activities) than the Garmin Fenix 5 and Fitbit Versa (for which the “Treadmill” mode was selected for all activities).

Conclusions

For measuring HR while sitting or during light-to-vigorous physical activity, the Apple Watch Series 4 exhibited the best validity (ie, the smallest error rates), followed by the Polar Vantage V, Garmin Fenix 5, and Fitbit Versa, in that order. The Apple Watch Series 4 and Polar Vantage V can be used for valid HR measurements at the intensities tested, whereas HR acquired with the Garmin Fenix 5 and Fitbit Versa must be interpreted cautiously due to their higher rates of error.

None of these wrist-worn wearables should be used to monitor EE at the intensities and durations tested.

Acknowledgments

We would like to thank Engelhorn Sports GmbH for their support. This study was funded by the German Research Foundation (DFG) and the University of Wuerzburg in the funding program Open Access Publishing. This study was partly funded by the excellence initiative “Field of Focu 4: Self-Regulation and Regulation” at the Heidelberg University (Grant No. ZUK49/2 Ü).

Conflicts of Interest

BS received funding from Polar Electro in connection with a previous project unrelated to the present investigation. The results of this study are presented clearly, honestly, and without fabrication, falsification, or inappropriate manipulation of data.

References

1. World Health Organization. 2018 Feb 23. Physical activity URL: http://www.who.int/mediacentre/factsheets/fs385/en/ [accessed 2020-03-07]
2. World Health Organization. 2010. Global recommendations on physical activity for health URL: https://www.who.int/dietphysicalactivity/factsheet_recommendations/en/ [accessed 2020-03-07]
3. World Health Organization. World Health Organization. 2020 Mar 03. Obesity and overweight URL: https://www.who.int/en/news-room/fact-sheets/detail/obesity-and-overweight [accessed 2020-03-07]
4. World Health Organization. 2018. Global action plan on physical activity 2018?2030: more active people for a healthier world URL: https://www.who.int/ncds/prevention/physical-activity/global-action-plan-2018-2030/en/ [accessed 2020-03-07]
5. Redenius N, Kim Y, Byun W. Concurrent validity of the Fitbit for assessing sedentary behavior and moderate-to-vigorous physical activity. BMC Med Res Methodol 2019 Feb 07;19(1):29 [FREE Full text] [doi: 10.1186/s12874-019-0668-1] [Medline: 30732582]
6. Trost SG. Objective measurement of physical activity in youth: current issues, future directions. Exerc Sport Sci Rev 2001;29(1):32-36. [doi: 10.1097/00003677-200101000-00007] [Medline: 11210445]
7. Seiler S. What is best practice for training intensity and duration distribution in endurance athletes? Int J Sports Physiol Perform 2010 Sep;5(3):276-291. [doi: 10.1123/ijspp.5.3.276] [Medline: 20861519]
8. Swain DP, Abernathy KS, Smith CS, Lee SJ, Bunn SA. Target heart rates for the development of cardiorespiratory fitness. Medicine & Science in Sports & Exercise 1994;26(1):112-116. [doi: 10.1249/00005768-199401000-00019]
9. Donnelly JE, Blair SN, Jakicic JM, Manore MM, Rankin JW, Smith BK. Appropriate Physical Activity Intervention Strategies for Weight Loss and Prevention of Weight Regain for Adults. Medicine & Science in Sports & Exercise 2009;41(2):459-471. [doi: 10.1249/mss.0b013e3181949333]
10. KOEHLER K, BRAUN H, DE MARÉES M, FUSCH G, FUSCH C, SCHAENZER W. Assessing Energy Expenditure in Male Endurance Athletes. Medicine & Science in Sports & Exercise 2011;43(7):1328-1333. [doi: 10.1249/mss.0b013e31820750f5]
11. Waldrop MM. The chips are down for Moore's law. Nature 2016 Feb 11;530(7589):144-147. [doi: 10.1038/530144a] [Medline: 26863965]
12. Thompson WR. WORLDWIDE SURVEY OF FITNESS TRENDS FOR 2019. ACSM s Health & Fitness Journal 2018;22(6):10-17. [doi: 10.1249/fit.0000000000000438]
13. Gal R, May AM, van Overmeeren EJ, Simons M, Monninkhof EM. The Effect of Physical Activity Interventions Comprising Wearables and Smartphone Applications on Physical Activity: a Systematic Review and Meta-analysis. Sports Med Open 2018 Sep 03;4(1):42 [FREE Full text] [doi: 10.1186/s40798-018-0157-9] [Medline: 30178072]
14. Düking P, Achtzehn S, Holmberg H, Sperlich B. Integrated Framework of Load Monitoring by a Combination of Smartphone Applications, Wearables and Point-of-Care Testing Provides Feedback that Allows Individual Responsive Adjustments to Activities of Daily Living. Sensors (Basel) 2018 May 19;18(5):1632 [FREE Full text] [doi: 10.3390/s18051632] [Medline: 29783763]
15. Techniker Krankenkasse. URL: https://www.tk.de/tk/themen/digitale-gesundheit/gesundheitsfoederung-durch-fitnesstracker-interview-dr-jens-baas/931248 [accessed 2018-04-04] [WebCite Cache ID 6yQE4yKX4]
16. World Health Organization. Addressing Mobile Health URL: https://www.who.int/ncds/prevention/be-healthy-be-mobile/en/ [accessed 2020-02-25]
17. Deutscher Bundestag. 2019 Sep 23. Entwurf eines Gesetzes für eine bessere Versorgung durch Digitalisierung und Innovation URL: https://www.bundesgesundheitsministerium.de/fileadmin/Dateien/3_Downloads/Gesetze_und_Verordnungen/GuV/D/DVG_Bundestag.pdf [accessed 2020-03-07]
18. Sperlich B, Holmberg H. Wearable, yes, but able…?: it is time for evidence-based marketing claims!. Br J Sports Med 2017 Aug 16;51(16):1240-1240 [FREE Full text] [doi: 10.1136/bjsports-2016-097295] [Medline: 27986762]
19. IDC. 2019 Sep 12. Wrist-Worn Wearables Maintain a Strong Growth Trajectory in Q2 2019, According to IDC URL: https://www.idc.com/getdoc.jsp?containerId=prUS45521319 [accessed 2019-11-29]
20. Düking P, Hotho A, Holmberg H, Fuss FK, Sperlich B. Comparison of Non-Invasive Individual Monitoring of the Training and Health of Athletes with Commercially Available Wearable Technologies. Front Physiol 2016 Mar 09;7:71 [FREE Full text] [doi: 10.3389/fphys.2016.00071] [Medline: 27014077]
21. Evenson KR, Goto MM, Furberg RD. Systematic review of the validity and reliability of consumer-wearable activity trackers. Int J Behav Nutr Phys Act 2015 Dec 18;12(1):159 [FREE Full text] [doi: 10.1186/s12966-015-0314-1] [Medline: 26684758]

22. Düking P, Fuss FK, Holmberg H, Sperlich B. Recommendations for Assessment of the Reliability, Sensitivity, and Validity of Data Provided by Wearable Sensors Designed for Monitoring Physical Activity. JMIR Mhealth Uhealth 2018 Apr 30;6(4):e102 [FREE Full text] [doi: 10.2196/mhealth.9341] [Medline: 29712629]
23. Düking P, Born DP, Sperlich B. The SpeedCourt: Reliability, Usefulness, and Validity of a New Method to Determine Change-of-Direction Speed. Int J Sports Physiol Perform 2016 Jan;11(1):130-134. [doi: 10.1123/ijspp.2015-0174] [Medline: 26061971]
24. Vogler AJ, Rice AJ, Gore CJ. Validity and reliability of the Cortex MetaMax3B portable metabolic system. J Sports Sci 2010 May;28(7):733-742. [doi: 10.1080/02640410903582776] [Medline: 20419553]
25. Wahl Y, Düking P, Droszez A, Wahl P, Mester J. Criterion-Validity of Commercially Available Physical Activity Tracker to Estimate Step Count, Covered Distance and Energy Expenditure during Sports Conditions. Front Physiol 2017 Sep 22;8:725 [FREE Full text] [doi: 10.3389/fphys.2017.00725] [Medline: 29018355]
26. Hermand E, Cassirame J, Ennequin G, Hue O. Validation of a Photoplethysmographic Heart Rate Monitor: Polar OH1. Int J Sports Med 2019 Jul 12;40(7):462-467. [doi: 10.1055/a-0875-4033] [Medline: 31189190]
27. Schubert M, Clark A, De La Rosa A. The Polar OH1 Optical Heart Rate Sensor is Valid during Moderate-Vigorous Exercise. Sports Med Int Open 2018 Jun 17;2(3):E67-E70 [FREE Full text] [doi: 10.1055/a-0631-0920] [Medline: 30539120]
28. Hopkins W. Spreadsheets for analysis of validity and reliability. Sportscience 2017;21.
29. Khushhal A, Nichols S, Evans W, Gleadall-Siddall D, Page R, O'Doherty A, et al. Validity and Reliability of the Apple Watch for Measuring Heart Rate During Exercise. Sports Med Int Open 2017 Oct 18;1(6):E206-E211 [FREE Full text] [doi: 10.1055/s-0043-120195] [Medline: 30539109]
30. Hopkins W. Validity thresholds and error rates for test measures used to assess individuals. In: Proceedings of the 21st Annual Congress of the European College of Sport Science. 2016 Jun 6 Presented at: 21st Annual Congress of the European College of Sport Science; 2016; Vienna, Austria.
31. Ainsworth BE, Haskell WL, Whitt MC, Irwin ML, Swartz AM, Strath SJ, et al. Compendium of physical activities: an update of activity codes and MET intensities. Med Sci Sports Exerc 2000 Sep;32(9 Suppl):S498-S504. [doi: 10.1097/00005768-200009001-00009] [Medline: 10993420]
32. BOUDREAUX BD, HEBERT EP, HOLLANDER DB, WILLIAMS BM, CORMIER CL, NAQUIN MR, et al. Validity of Wearable Activity Monitors during Cycling and Resistance Exercise. Medicine & Science in Sports & Exercise 2018;50(3):624-633. [doi: 10.1249/mss.0000000000001471]
33. Dooley EE, Golaszewski NM, Bartholomew JB. Estimating Accuracy at Exercise Intensities: A Comparative Study of Self-Monitoring Heart Rate and Physical Activity Wearable Devices. JMIR Mhealth Uhealth 2017 Mar 16;5(3):e34 [FREE Full text] [doi: 10.2196/mhealth.7043] [Medline: 28302596]
34. Thomson EA, Nuss K, Comstock A, Reinwald S, Blake S, Pimentel RE, et al. Heart rate measures from the Apple Watch, Fitbit Charge HR 2, and electrocardiogram across different exercise intensities. J Sports Sci 2019 Jun 18;37(12):1411-1419. [doi: 10.1080/02640414.2018.1560644] [Medline: 30657025]
35. Bai Y, Hibbing P, Mantis C, Welk GJ. Comparative evaluation of heart rate-based monitors: Apple Watch vs Fitbit Charge HR. J Sports Sci 2018 Aug 06;36(15):1734-1741. [doi: 10.1080/02640414.2017.1412235] [Medline: 29210326]
36. Kinnunen H, Häkkinen K, Schumann M, Karavirta L, Westerterp KR, Kyröläinen H. Training-induced changes in daily energy expenditure: Methodological evaluation using wrist-worn accelerometer, heart rate monitor, and doubly labeled water technique. PLoS One 2019 Jul 10;14(7):e0219563 [FREE Full text] [doi: 10.1371/journal.pone.0219563] [Medline: 31291373]
37. Keytel L, Goedecke J, Noakes T, Hiiloskorpi H, Laukkanen R, van der Merwe L, et al. Prediction of energy expenditure from heart rate monitoring during submaximal exercise. J Sports Sci 2005 Mar 18;23(3):289-297. [doi: 10.1080/02640410470001730089] [Medline: 15966347]
38. The Department of Health, Australian Government. 2019 Apr 12. Australia's Physical Activity and Sedentary Behaviour Guidelines and the Australian 24-Hour Movement Guidelines URL: https://www1.health.gov.au/internet/main/publishing.nsf/Content/health-pubhlth-strateg-phys-act-guidelines [accessed 2020-07-03]
39. US Department of Health and Human Services. 2018. Physical Activity Guidelines for Americans 2nd Edition URL: https://health.gov/paguidelines/second-edition/pdf/Physical_Activity_Guidelines_2nd_edition.pdf [accessed 2020-03-07]
40. Jenkins EM, Nairn LN, Skelly LE, Little JP, Gibala MJ. Do stair climbing exercise "snacks" improve cardiorespiratory fitness? Appl Physiol Nutr Metab 2019 Jun;44(6):681-684. [doi: 10.1139/apnm-2018-0675] [Medline: 30649897]

Abbreviations

CV: coefficient of variation.
EE: energy expenditure.
HR: heart rate.
MET: metabolic equivalent.
sTEE: standardized typical error of the estimate.
WHO: World Health Organization.

Edited by G Eysenbach; submitted 21.10.19; peer-reviewed by L Ardigò, E Kemler; comments to author 25.11.19; revised version received 12.12.19; accepted 24.01.20; published 05.04.20

Please cite as:
Düking P, Giessing L, Frenkel MO, Köhler K, Holmberg HC, Sperlich B
Wrist-worn Wearables for Monitoring Heart Rate and Energy Expenditure While Sitting or Performing Light-to-vigorous Physical Activity: Validation Study
JMIR Mhealth Uhealth 2020;8(4):e16716
URL: http://mhealth.jmir.org/2020/4/e16716/
doi: 10.2196/16716
PMID:

sensors

MDPI

Article

Integrated Framework of Load Monitoring by a Combination of Smartphone Applications, Wearables and Point-of-Care Testing Provides Feedback that Allows Individual Responsive Adjustments to Activities of Daily Living

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Received: 20 March 2018; Accepted: 4 May 2018; Published: 19 May 2018

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Abstract: Athletes schedule their training and recovery in periods, often utilizing a pre-defined strategy. To avoid underperformance and/or compromised health, the external load during training should take into account the individual's physiological and perceptual responses. No single variable provides an adequate basis for planning, but continuous monitoring of a combination of several indicators of internal and external load during training, recovery and off-training as well may allow individual responsive adjustments of a training program in an effective manner. From a practical perspective, including that of coaches, monitoring of potential changes in health and performance should ideally be valid, reliable and sensitive, as well as time-efficient, easily applicable, non-fatiguing and as non-invasive as possible. Accordingly, smartphone applications, wearable sensors and point-of-care testing appear to offer a suitable monitoring framework allowing responsive adjustments to exercise prescription. Here, we outline 24-h monitoring of selected parameters by these technologies that (i) allows responsive adjustments of exercise programs, (ii) enhances performance and/or (iii) reduces the risk for overuse, injury and/or illness.

Keywords: biofeedback; eHealth; individualized training; injury prevention; IoT; load management; periodization

1. Introduction

To optimize performance, athletes schedule their training and recovery in periods, i.e., in micro- (e.g., within a single session of training or from day-to-day) or macro-cycles (e.g., on a weekly or monthly basis), with variations in intensity, volume and/or frequency.

Adaptation (e.g., with respect to elevated power output or oxygen uptake) to standardized training varies considerably between individuals [1,2]. Rigid adherence to a standardized or pre-defined program of exercise, without routine monitoring of physiological and perceptual responses and appropriate responsive adjustments, may result in underperformance and/or compromise health [3]. The training stimulus becomes inappropriate when the external load (defined here as the work/physical activity completed) is unsuited to the psycho–physiological responses of the individual involved (referred to here as the internal load) [4,5].

Monitoring load is extremely complex, since all of an individual's systems adapt to numerous simultaneous stimuli in an integrated manner. It has been proposed that 24-h monitoring might help take into account the various factors that influence overall adaptation to exercise, thereby improving our insight into the interdependencies in this context between the stress of training, recovery, off-training activities of daily-life, and various other stimuli (e.g., temperature, humidity, psycho-social stressors, and many more) [6] and may allow individual responsive adjustments to exercise programming. From a practical perspective, including that of coaches, monitoring of load designed to detect potential changes in health and performance should be valid, reliable and sensitive, as well as time-efficient, easily applicable, non-fatiguing and as non-invasive as possible [7].

In this context, smartphone applications (Apps), wearable sensors (Wearables) and point-of-care-testing (POCT) all allow (i) high-resolution and/or regular monitoring of a variety of relevant psycho–physiological markers of internal and external load; (ii) minimally or non-invasive collection of data; (iii) rapid evaluation of this data and, thereby, potentially instant (bio-)feedback; (iv) measurements in a variety of different settings (e.g., at home, while training, during competition, while traveling, during daily-living); and/or (v) monitoring without the involvement of sophisticated medical personnel or the necessity for a laboratory [8–10].

Interestingly, despite these considerable advantages, there appears to be little awareness of the capabilities of Apps, Wearables and POCT to provide integrated and instant feedback to athletes and coaches that allows adjustment of exercise to minimize risks to health and optimize adaptation. Accordingly, the present aim was to describe certain approaches of this nature that might be effective.

2. Monitoring Parameters of External and Internal Load

The various parameters associated with external and internal training load all appear to be of potential interest in connection with monitoring responses [4,8,11]. Here, we focus on external parameters which describe the workload completed by an individual and internal psycho-physiological indicators which can assist coaches in modifying the external load in an appropriate manner. We have focused on load parameters currently monitored by Apps, Wearables, and/or POCT devices by minimally or non-invasive sampling of capillary blood or saliva, since such sampling does not require trained medical personnel. Although certain of their characteristics do overlap, we define Apps as executable software running on a handheld device such as smartphones and, sometimes, smartwatches; Wearables as lightweight devices worn close to, on or in the body that monitor, transmit and/or analyse data, providing bio-feedback [8], while POCT devices allow rapid biochemical, haematological, coagulation or molecular diagnostics at the point-of-care (e.g., the training facility), often in a minimally invasive manner [9].

It is beyond the present scope to consider all possible parameters and those we have chosen to focus on here are listed in Table 1 (external parameters) and Table 2 (internal parameters). While we motivate these choices, we are certainly aware that future technological advancements may well open more sophisticated perspectives.

3. Monitoring External Parameters

3.1. The Duration and Frequency of Training Sessions

The duration and frequency of exercise sessions, important and simple indicators of external load, can be easily monitored by (sport) watches. Many manufacturers provide the possibility to store this data automatically in a (cloud-based) database, which makes collection, aggregation and visualisation simple and straightforward.

Table 1. Important external parameters and metrics that can be monitored by Apps and Wearables.

Type of Parameter	Individual Parameters	Method/Sensor Technology	Additional Comments
Duration and frequency of training sessions	- Time - Number	Sport watches	Sport watches allow automatic storage of data in the "cloud"
Distance covered (in different speed zones)	e.g., - absolute value - relative value - acute:chronic workload ratio	Global Navigation Satellite Systems	- Only useful outdoors - High sampling frequency required
		Local positioning systems	In- and outdoors
Short explosive activities	e.g., - absolute accelerations - relative accelerations	Inertial measurement units	Embedded in a Global Navigation Satellite System receiver unit
Sleep	- Quantity - Circadian rhythm	Actigraphy	Actigraphy should only be used with caution to access sleep quality.
Environmental factors	- Temperature - Altitude - Ultra-violet radiation - Humidity	- Thermometer - Barometer - Hygrometer	

Table 2. Important internal parameters and metrics that can be monitored by Apps, Wearables and point-of-care-testing.

Type of Parameter	Individual Parameter	Area of Interest
General health	Core, body or skin temperature	Thermoregulation
	White blood cell count	Infections
	High-sensitive C-reactive Protein	Inflammation
	Immunoglobulin A (IglA)	Mucosal immune function
	Reactive Oxygen Species	Oxidative stress
	Haemoglobin	Anaemia and dehydration
	Ferritin	Iron deficiency
Bio-psychological stress	Cortisol	- Protein degradation - Suppression of immune function
	Alpha-amylase	Stress on the sympathetic nervous system
Subjective parameters	Questionnaires and diaries	Various psychological aspects
Parameters of cardiac stress	Cardiac troponin	Myocardial stress
	Fatty acid-binding protein	
	Heart rate during exercise	
	Heart rate variability	Cardiac autonomous nervous system
	Heart rate recovery	Overreaching
Parameters of muscle damage	Aspartate aminotransferase	Breakdown of muscle cell structureProtein catabolism
	Creatine kinase	
	Myoglobin	
	Lactate dehydrogenase	
Parameters of metabolism	Lactate	Endurance performance
	Urea	Elevated protein catabolism
	Uric acid	Enhanced metabolic strain when muscle stores of glycogen are depleted
	Creatinine	Renal functioning
	Testosterone	Non-functional overreaching
	Tissue oxygenation	Intensity of effort
	pH	Acid-base status

3.2. Distance Covered

For many athletes the distance covered and time spent in different speed zones (expressed either in absolute or relative terms or as ratios, i.e., the acute/chronic workload ratio = the ratio of the workload during a single week to the average workload during a period of approximately four weeks) allow quantification of the external load and the distance covered exhibits a positive correlation to the likelihood of injury [12–14]. Relatively comfortable Wearable receiver units and Apps assess distance-related parameters employing global navigation satellite systems (GNSS) or local positioning systems (LPS).

3.3. Short Explosive Activities

Short explosive activities, such as movements involving a change in direction [15], tackling [16], sprinting [17] or throwing [18], may be utilized as measures of external load. For this purpose, three-dimensional accelerometers and gyroscopes that can be incorporated into various devices monitor parameters of body acceleration that can then be expressed in absolute or relative accumulated terms (44,40,45). For example, since the performance of numerous throws or tackling manoeuvres elevates the risk for injury [16,18,19], short explosive activities should be monitored closely.

3.4. Environmental Factors

A variety of environmental factors, including altitude, inclination, slope, temperature, exposure to ultra-violet radiation and humidity [20,21], can all exert a significant impact on external loading. These factors are readily monitored by sensors in Wearables.

3.5. Sleep

Developing research regarding sleep in athletes [22] reveals that sleep, performance and/or health are interconnected [23], as would be expected. The length of sleep and its relationship to the circadian rhythm can be estimated from the data supplied by Apps and Wearables employing various procedures [8,24,25].

3.6. Physical Activity Off-Training

Periods of off-training are often scheduled in a manner designed to optimize recovery and it is generally accepted that the type of activity (e.g., passive versus active) engaged in after exercise influences this recovery [26] and is therefore important to monitor [27]. Apps [28] and/or Wearables [29] can monitor off-training physical activity with, e.g., accelerometers and/or GPS-receivers and/or by photoplethysmography. Our knowledge concerning how off-training activities affect performance and/or health is presently seriously limited and needs to be extended.

4. Monitoring Internal Load

4.1. Parameters of General Health

Absence of illness and injury are obviously essential for athletic success. Several (sophisticated) parameters that reflect an athlete's general health, level of stress and immunological status can all be assessed by, Wearables and/or POCT in a minimally or non-invasive manner. For instance, Wearables detect skin and body temperature at rest and during exercise, e.g., to assess heat-induced fatigue, and/or illness, as well as fever [30,31]. Various POCT devices can monitor such health-related variables as the white blood cell count (WBC; including determination of sub-populations and indicative of potential inflection) [32], high-sensitive C-reactive protein (hs-CRP, a marker of inflammation) and salivary immunoglobulin A (SIgA) (an indicator of mucosal immunity) [33]. In addition, POCT can detect toxic reactive oxygen species (ROS) produced during inflammation or exercise [34].

The blood level of haemoglobin, a crucial determinant of oxygen delivery, is influenced by the availability of iron and, thus, by the iron-storage protein ferritin. Prolonged and intense exercise is well known to stimulate rapid turn-over of erythrocytes, thereby causing loss of ferritin and a consequent reduction in the concentration of haemoglobin [35,36]. Monitoring of ferritin by POCT provides information about the transport of oxygen by the blood, allowing detection, e.g., of premature exhaustion. Furthermore, low levels of haemoglobin may reflect anaemia, whereas elevated levels may be indicative of dehydration.

4.2. Parameters Related to Cardiac Dynamics and Stress

With heart rate as a basis, Wearables can provide information on different parameters related to cardiac dynamics and stress [8,37]. Heart rate during exercise (expressed relative to an individual's maximum) is often employed to quantify the intensity of exercise and can be used to monitor aerobic adaptation [37]. Variability in the heart rate (defined as the time that elapses between two consecutive R-R intervals) provides insight into the innervation of the heart by the autonomous nervous system [37–39] and appears to be relevant to chronic stress [40]. Such variability can be monitored by Wearables using different technologies [8], as long as potential confounding factors are carefully controlled for [37,41]. Heart rate recovery might indicate overreaching in athletes [42]. In addition, markers of potential myocardial stress, such as troponin and fatty-acid-binding protein (FABP), can be analysed by POCT [43].

4.3. Parameters Related to Bio-Psychological Stress

Elevated levels of salivary cortisol and alpha-amylase, both of which can be monitored readily by POCT, are indicative of internal stress [44,45]. This cortisol level increases in response to intense physical exercise. Elevated levels of cortisol, which is considered to be the hormone primarily responsible for catabolic processes, can augment protein degradation, attenuate protein synthesis, and dampen inflammation and immunity [46,47]. Alpha-amylase activates the sympathetic nervous system [45] and exhibits diurnal variations, with its level in saliva being more sensitive to exercise-induced stress than that of cortisol [43]. Alpha-amylase also contributes to innate mucosal immunity [46,48,49].

4.4. Subjective Parameters

Assessment of subjective psycho-emotional variables [2], including self-reported sleep [50], perceived exertion [51] and general well-being, are crucial components of the monitoring of recovery and stress [11,52]. Although subjective indicators tend to be more sensitive to acute and chronic training loads than objective ones [11], the former can be more easily manipulated to achieve the outcomes desired.

Apps can be programmed to use touch or voice-controlled user-interfaces to monitor various subjective variables in a convenient manner.

4.5. Neuromuscular Variables

Applied properly [8], Wearables can detect neuronal activation of muscles that reflects neuromuscular fatigue [53]. POCT can be employed to measure blood levels of, e.g., aspartate aminotransferase, lactate dehydrogenase, creatine kinase, and myoglobin, classical markers of muscular load [54,55], with elevated levels indicating muscle damage and rhabdomyolysis. Since the kinetics of these levels vary, these parameters should be assessed in conjunction with the external load.

4.6. Parameters Related to Metabolism

Wearables can measure muscle oxygenation [8], thereby providing an estimate of local oxygen delivery and/or providing insights into muscular responses to exercise [56]. POCT can be utilized to measure blood levels of urea, uric acid and creatinine as reflections of metabolic processes. Urea in the capillary blood is indicative of augmented protein catabolism and gluconeogenesis [57,58]. An elevated level of uric acid, the terminal product of purine metabolism, is indicative of enhanced metabolism when muscle stores of glycogen have been depleted [55,57]. Creatinine levels provide information concerning renal functioning, which is of particular interest in situations where a proper electrolyte balance is crucial [55]. Levels of lactate can be monitored easily by both POCT devices and Wearables [59] and different lactate thresholds have been utilized as estimates of endurance performance [60].

POCT devices can also measure the partial pressures of oxygen and carbon dioxide in, as well as the pH of the blood, all important load variables e.g., in connection with hypoxic exposure [43].

POCT-assessed quantification of testosterone in the saliva may allow assessment of non-functional overtraining [46]. Moreover, the ratio of testosterone to cortisol provides further insight into the metabolic state (i.e., catabolic or anabolic) [43,61].

5. Practical Procedure for Monitoring Relevant Parameters

Figure 1 illustrates a procedure for individualized management of load and recovery designed to optimize performance and/or minimize the risk of overuse, injury and/or illnesses.

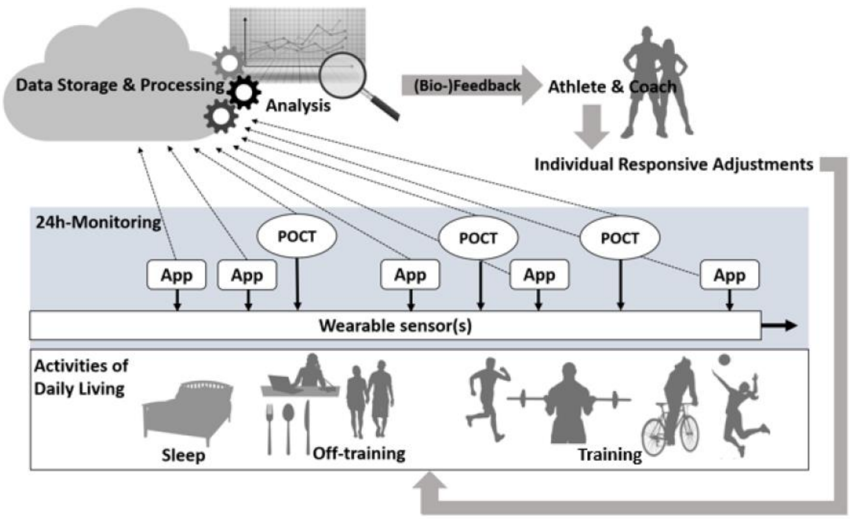

Figure 1. Procedure for monitoring external and internal training load employing Apps, Wearables and POCT and providing feedback to athletes and their coaches that allows beneficial responsive modification of exercise programs.

Wearables allow unobtrusive and continuous monitoring of parameters during training, recovery and periods of off-training [6], as well as, if approved by regulatory bodies [62], during actual competitions.

Apps that collect subjective data and require little compliance may be used selectively per day e.g., in the morning or before or after a training session. Since POCT requires sampling of capillary blood or saliva and the levels measured may show circadian variation, collection of such data daily or at shorter intervals might not be feasible. Since no individual App, Wearable or POCT device on its own can monitor all of the parameters mentioned above, in our opinion a combination of these devices is required in order to achieve a more holistic view of the various physiological, biomechanical and psychological responses of an athlete. It appears advantageous to incorporate at least wearable sensors into a body sensor network which is part of a fully integrated multiplexed sensing system [63], i.e., a central body unit connected wirelessly to various sensor nodes and cloud services that pre-format and synchronize relevant data [63,64], to facilitate user handling of several wearables at the same time.

The selection of parameters, as well as the timing and frequency of their monitoring clearly depends on the sport involved, the scientific basis for measurement, whether the individual is training or competing, and the extent to which the athlete and his/her coach accept and/or are aware of the benefits and drawbacks of monitoring with Apps, Wearables, and POCT.

It is beyond our present scope to discuss the numerous and rapidly changing technologies and algorithms involved in Apps, Wearables and/or POCT devices and, therefore, we refer practitioners to information concerning the advantages and disadvantages of each [8,65]. Currently, there are few reports involving 24-h monitoring in a sports setting [27,66] and more research in this area is clearly warranted.

As the amount of data collected increases, more effective systems for analysis, interpretation and reporting simple, yet meaningful results to athletes and coaches are necessary. With advancements in the analysis of large datasets, suitable algorithms may allow novel insights into the relationships between the parameters monitored and various aspects of performance and/or health. To further improve the framework outlined, we propose that future developments must allow the monitoring of additional parameters non-invasively by Wearables and/or Apps to collect as much data as reliable and as conveniently as possible. Moreover, an easy-to-use system that ideally incorporates all of the parameters mentioned above to provide simple, but powerful feedback to the practitioner is required.

Only if the data collected are stored securely to avoid misuse [67] can the framework outlined be employed successfully by stakeholders.

6. Practical Considerations

In this overview we have proposed a procedure for assessing markers of external and internal load by Wearables, Apps and/or POCT in a minimally or non-invasive manner designed to adapt training programs in order to optimize performance and/or minimize the risk of injury and/or illness. However, we have not taken certain other parameters usually monitored by other (invasive) procedures (e.g., venous blood sampling or muscle biopsies) into consideration. Furthermore, we have not discussed the methods and analytical algorithms involved extensively. Since different technologies and algorithms probably provide different results, we advise practitioners to carefully check the reliability and validity of each device of interest carefully following outlined recommendations prior to application in a routine monitoring [68,69] Moreover, when choosing a Wearable, App or POCT device for use, practical considerations such as the costs of the device(s) and of each measurement, as well as the time required for analysis, battery life, options for transfer of data and data security must be taken into consideration.

Finally, we want to emphasize that a framework as suggested here will vary depending on the technology employed, training status, sport and individual goals and most notably the framework does not replace coaching intelligence and the athlete's experience but may assist to enhance performance and/or to reduce the risk of overuse, injury and/or illness.

7. Conclusions

Here, we summarize external and internal parameters that can be obtained by Apps, Wearables, and/or POCT and utilized to enhance athletic performance and/or reduce the likelihood of injury and/or illness; we also propose a procedure for such monitoring. For practical purposes, a sophisticated data management system will be required, as well as additional evaluation of the relationships between various parameters and performance and/or health.

Author Contributions: Conceptualization, P.D., S.A. and B.S.; Methodology, P.D., S.A., H-C. H., and B.S.; Writing-Original Draft Preparation, P.D., S.A., B.S.; Writing-Review & Editing, P.D., S.A., H-C. H., and B.S.; Supervision, P.D. and B.S.; Project Administration, P.D. and B.S..

Funding: This study was funded by the German Research Foundation (DFG) and the University of Wuerzburg in the funding programme Open Access Publishing.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Skinner, J.S.; Wilmore, K.M.; Krasnoff, J.B.; Jaskolski, A.; Jaskolska, A.; Gagnon, J.; Province, M.A.; Leon, A.S.; Rao, D.C.; Wilmore, J.H.; et al. Adaptation to a standardized training program and changes in fitness in a large, heterogeneous population: The HERITAGE Family Study. *Med. Sci. Sports Exerc.* **2000**, *32*, 157–161. [CrossRef] [PubMed]
2. Kiely, J. Periodization Theory: Confronting an Inconvenient Truth. *Sports Med.* **2018**, *48*, 753–764. [CrossRef] [PubMed]
3. Soligard, T.; Schwellnus, M.; Alonso, J.M.; Bahr, R.; Clarsen, B.; Dijkstra, H.P.; Gabbett, T.; Gleeson, M.; Hägglund, M.; Hutchinson, M.R. How much is too much? (Part 1) International Olympic Committee consensus statement on load in sport and risk of injury. *Br. J. Sports Med.* **2016**, *50*, 1030–1041. [CrossRef] [PubMed]
4. Halson, S.L. Monitoring training load to understand fatigue in athletes. *Sports Med.* **2014**, *44*, S139–S147. [CrossRef] [PubMed]
5. Mujika, I. Quantification of Training and Competition Loads in Endurance Sports: Methods and Applications. *Int. J. Sports Physiol. Perform.* **2017**, *12*, S2-9–S2-17. [CrossRef] [PubMed]
6. Sperlich, B.; Holmberg, H.C. The Responses of Elite Athletes to Exercise: An All-Day, 24-h Integrative View Is Required! *Front. Physiol.* **2017**, *8*, 564. [CrossRef] [PubMed]
7. Starling, L.T.; Lambert, M.I. Monitoring Rugby Players for Fitness and Fatigue: What Do Coaches Want? *Int. J. Sports Physiol. Perform.* **2017**, *15*, 1–30. [CrossRef] [PubMed]
8. Düking, P.; Hotho, A.; Holmberg, H.C.; Fuss, F.K.; Sperlich, B. Comparison of non-invasive individual monitoring of the training and health of athletes with commercially available wearable technologies. *Front. Physiol.* **2016**, *7*, 71. [CrossRef] [PubMed]
9. Luppa, P.B.; Bietenbeck, A.; Beaudoin, C.; Giannetti, A. Clinically relevant analytical techniques, organizational concepts for application and future perspectives of point-of-care testing. *Biotechnol. Adv.* **2016**, *34*, 139–160. [CrossRef] [PubMed]
10. Düking, P.; Holmberg, H.C.; Sperlich, B. Instant biofeedback provided by wearable sensor technology can help to optimize exercise and prevent injury and overuse. *Front. Physiol.* **2017**, *8*, 167. [CrossRef] [PubMed]
11. Saw, A.E.; Main, L.C.; Gastin, P.B. Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: A systematic review. *Br. J. Sports Med.* **2016**, *50*, 281–291. [CrossRef] [PubMed]
12. Colby, M.J.; Dawson, B.; Heasman, J.; Rogalski, B.; Gabbett, T.J. Accelerometer and GPS-derived running loads and injury risk in elite Australian footballers. *J. Strength Cond. Res.* **2014**, *28*, 2244–2252. [CrossRef] [PubMed]
13. Gabbett, T.J. The training-injury prevention paradox: Should athletes be training smarter and harder? *Br. J. Sports Med.* **2016**, *50*, 273–280. [CrossRef] [PubMed]
14. Ehrmann, F.E.; Duncan, C.S.; Sindhusake, D.; Franzsen, W.N.; Greene, D.A. GPS and Injury Prevention in Professional Soccer. *J. Strength Cond. Res.* **2016**, *30*, 360–367. [CrossRef] [PubMed]
15. Akenhead, R.; French, D.; Thompson, K.G.; Hayes, P.R. The physiological consequences of acceleration during shuttle running. *Int. J. Sports Med.* **2015**, *36*, 302–307. [CrossRef] [PubMed]
16. Kelly, D.; Coughlan, G.F.; Green, B.S.; Caulfield, B. Automatic detection of collisions in elite level rugby union using a wearable sensing device. *Sports Eng.* **2012**, *15*, 81–92. [CrossRef]
17. Cardinale, M.; Varley, M.C. Wearable Training-Monitoring Technology: Applications, Challenges, and Opportunities. *Int. J. Sports Physiol. Perform.* **2017**, *12*, S255–S2629. [CrossRef] [PubMed]
18. Murray, N.B.; Black, G.M.; Whiteley, R.J.; Gahan, P.; Cole, M.H.; Utting, A.; Gabbett, T.J. Automatic Detection of Pitching and Throwing Events in Baseball With Inertial Measurement Sensors. *Int. J. Sports Physiol. Perform.* **2017**, *12*, 533–537. [CrossRef] [PubMed]
19. Hendricks, S.; Lambert, M.I. Theoretical Model Describing the Relationship between the Number of Tackles in Which A Player Engages, Tackle Injury Risk and Tackle Performance. *J. Sports Sci. Med.* **2014**, *13*, 715–717. [PubMed]
20. Hargreaves, M. Physiological limits to exercise performance in the heat. *J. Sci. Med. Sport/Sports Med. Aust.* **2008**, *11*, 66–71. [CrossRef] [PubMed]

21. Born, D.P.; Hoppe, M.W.; Lindner, N.; Freiwald, J.; Holmberg, H.C.; Sperlich, B. Adaptive mechanisms and behavioural recommendations: Playing football in heat, cold and high altitude conditions. *Sportverletzung Sportschaden: Organ der Gesellschaft fur Orthopadisch-Traumatologische Sportmedizin* **2014**, *28*, 17–23. [CrossRef]
22. Taylor, L.; Chrismas, B.C.; Dascombe, B.; Chamari, K.; Fowler, P.M. The Importance of Monitoring Sleep within Adolescent Athletes: Athletic, Academic, and Health Considerations. *Front. Physiol.* **2016**, *7*, 101. [CrossRef] [PubMed]
23. Fullagar, H.H.; Skorski, S.; Duffield, R.; Hammes, D.; Coutts, A.J.; Meyer, T. Sleep and athletic performance: The effects of sleep loss on exercise performance, and physiological and cognitive responses to exercise. *Sports Med.* **2015**, *45*, 161–186. [CrossRef] [PubMed]
24. Min, Y.H.; Lee, J.W.; Shin, Y.W.; Jo, M.W.; Sohn, G.; Lee, J.H.; Lee, G.; Jung, K.H.; Sung, J.; Ko, B.S.; et al. Daily collection of self-reporting sleep disturbance data via a smartphone app in breast cancer patients receiving chemotherapy: A feasibility study. *J. Med. Internet Res.* **2014**, *16*, e135. [CrossRef] [PubMed]
25. Chen, Z.; Lin, M.; Chen, F.; Lane, N.D.; Cardone, G.; Wang, R.; Li, T.; Chen, Y.; Choudhury, T.; Campbel, A.T. Unobtrusive sleep monitoring using smartphones. In Proceedings of the 2013 7th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth), Venice, Italy, 5–8 May 2013.
26. Burr, J.F.; Slysz, J.T.; Boulter, M.S.; Warburton, D.E. Influence of Active Recovery on Cardiovascular Function During Ice Hockey. *Sports Med. Open* **2015**, *1*, 27. [CrossRef] [PubMed]
27. Sperlich, B.; Becker, M.; Hotho, A.; Wallmann-Sperlich, B.; Sareban, M.; Winkert, K.; Steinacker, J.M.; Treff, G. Sedentary Behavior among National Elite Rowers during Off-Training—A Pilot Study. *Front. Physiol.* **2017**, *8*, 655. [CrossRef] [PubMed]
28. DeMasi, O.; Feygin, S.; Dembo, A.; Aguilera, A.; Recht, B. Well-Being Tracking via Smartphone-Measured Activity and Sleep: Cohort Study. *JMIR mHealth uHealth* **2017**, *5*, e137. [CrossRef] [PubMed]
29. Wahl, Y.; Düking, P.; Droszez, A.; Wahl, P.; Mester, J. Criterion-Validity of Commercially Available Physical Activity Tracker to Estimate Step Count, Covered Distance and Energy Expenditure during Sports Conditions. *Front. Physiol.* **2017**, *8*, 725. [CrossRef] [PubMed]
30. Noakes, T. Fluid replacement during marathon running. *Clin. J. Sport Med.* **2003**, *13*, 309–318. [CrossRef] [PubMed]
31. Nakamura, K. Central circuitries for body temperature regulation and fever. *Am. J. Physiol. Regul. Integr. Comp. Physiol.* **2011**, *301*, R1207–R1228. [CrossRef] [PubMed]
32. Horn, P.L.; Pyne, D.B.; Hopkins, W.G.; Barnes, C.J. Lower white blood cell counts in elite athletes training for highly aerobic sports. *Eur. J. Appl. Physiol.* **2010**, *110*, 925–932. [CrossRef] [PubMed]
33. Born, D.P.; Faiss, R.; Willis, S.J.; Strahler, J.; Millet, G.P.; Holmberg, H.C.; Sperlich, B. Circadian variation of salivary immunoglobin A, alpha-amylase activity and mood in response to repeated double-poling sprints in hypoxia. *Eur. J. Appl. Physiol.* **2016**, *116*, 1–10. [CrossRef] [PubMed]
34. Gomes, E.C.; Silva, A.N.; de Oliveira, M.R. Oxidants, antioxidants, and the beneficial roles of exercise-induced production of reactive species. *Oxid. Med. Cell. Longev.* **2012**, *2012*, 756132. [CrossRef] [PubMed]
35. Peeling, P.; Dawson, B.; Goodman, C.; Landers, G.; Trinder, D. Athletic induced iron deficiency: New insights into the role of inflammation, cytokines and hormones. *Eur. J. Appl. Physiol.* **2008**, *103*, 381–391. [CrossRef] [PubMed]
36. Hinton, P.S. Iron and the endurance athlete. *Appl. Physiol. Nutr. Metab.* **2014**, *39*, 1012–1081. [CrossRef] [PubMed]
37. Buchheit, M. Monitoring training status with HR measures: Do all roads lead to Rome? *Front. Physiol.* **2014**, *5*, 73. [CrossRef] [PubMed]
38. Aubert, A.E.; Seps, B.; Beckers, F. Heart rate variability in athletes. *Sports Med.* **2003**, *33*, 889–919. [CrossRef] [PubMed]
39. Achten, J.; Jeukendrup, A.E. Heart rate monitoring: Applications and limitations. *Sports Med.* **2003**, *33*, 517–538. [CrossRef] [PubMed]
40. Dong, J.G. The role of heart rate variability in sports physiology. *Exp. Ther. Med.* **2016**, *11*, 1531–1536. [CrossRef] [PubMed]
41. Plews, D.J.; Laursen, P.B.; Le Meur, Y.; Hausswirth, C.; Kilding, A.E.; Buchheit, M. Monitoring training with heart rate-variability: How much compliance is needed for valid assessment? *Int. J. Sports Physiol. Perform.* **2014**, *9*, 783–790. [CrossRef] [PubMed]

42. Le Meur, Y.; Buchheit, M.; Aubry, A.; Coutts, A.J.; Hausswirth, C. Assessing Overreaching with HRR: What is the Minimal Exercise Intensity Required? *Int. J. Sports Physiol. Perform.* **2017**, *12*, 569–573. [CrossRef] [PubMed]
43. Achtzehn, S. *POCT-Patientennahe Labordiagnostik*; Luppa, P.B., Junker, R., Eds.; Springer Verlag: New York, NY, USA, 2017.
44. Dimitriou, L.; Sharp, N.C.; Doherty, M. Circadian effects on the acute responses of salivary cortisol and IgA in well trained swimmers. *Br. J. Sports Med.* **2002**, *36*, 260–264. [CrossRef] [PubMed]
45. Rohleder, N.; Nater, U.M. Determinants of salivary alpha-amylase in humans and methodological considerations. *Psychoneuroendocrinology* **2009**, *34*, 469–485. [CrossRef] [PubMed]
46. Papacosta, E.; Nassis, G.P. Saliva as a tool for monitoring steroid, peptide and immune markers in sport and exercise science. *J. Sci. Med. Sport/Sports Med. Aust.* **2011**, *14*, 424–434. [CrossRef] [PubMed]
47. McLellan, C.P.; Lovell, D.I.; Gass, G.C. Markers of postmatch fatigue in professional Rugby League players. *J. Strength Cond. Res./Natl. Strength Cond. Assoc.* **2011**, *25*, 1030–1039. [CrossRef] [PubMed]
48. Koibuchi, E.; Suzuki, Y. Exercise upregulates salivary amylase in humans (Review). *Exp. Ther. Med.* **2014**, *7*, 773–777. [CrossRef] [PubMed]
49. Nater, U.M.; Rohleder, N.; Schlotz, W.; Ehlert, U.; Kirschbaum, C. Determinants of the diurnal course of salivary alpha-amylase. *Psychoneuroendocrinology* **2007**, *32*, 392–401. [CrossRef] [PubMed]
50. Sargent, C.; Lastella, M.; Halson, S.L.; Roach, G.D. The impact of training schedules on the sleep and fatigue of elite athletes. *Chronobiol. Int.* **2014**, *31*, 1160–1168. [CrossRef] [PubMed]
51. Foster, C.; Florhaug, J.A.; Franklin, J.; Gottschall, L.; Hrovatin, L.A.; Parker, S.; Doleshal, P.; Dodge, C. A new approach to monitoring exercise training. *J. Strength Cond. Res./Natl. Strength Cond. Assoc.* **2001**, *15*, 109–115.
52. Kellmann, M. Preventing overtraining in athletes in high-intensity sports and stress/recovery monitoring. *Scand. J. Med. Sci. Sports* **2010**, *20* (Suppl. 2), 95–102. [CrossRef] [PubMed]
53. Abbiss, C.R.; Laursen, P.B. Models to explain fatigue during prolonged endurance cycling. *Sports Med.* **2005**, *35*, 865–898. [CrossRef] [PubMed]
54. Brancaccio, P.; Lippi, G.; Maffulli, N. Biochemical markers of muscular damage. *Clin. Chem. Lab. Med.* **2010**, *48*, 757–767. [CrossRef] [PubMed]
55. Banfi, G.; Colombini, A.; Lombardi, G.; Lubkowska, A. Metabolic markers in sports medicine. *Adv. Clin. Chem.* **2012**, *56*, 1–54. [PubMed]
56. Born, D.P.; Stoggl, T.; Swaren, M.; Bjorklund, G. Running in Hilly Terrain: NIRS is More Accurate to Monitor Intensity than Heart Rate. *Int. J. Sports Physiol. Perform.* **2016**, *24*, 1–21. [CrossRef]
57. Meister, S.; Faude, O.; Ammann, T.; Schnittker, R.; Meyer, T. Indicators for high physical strain and overload in elite football players. *Scand. J. Med. Science Sports* **2013**, *23*, 156–1633. [CrossRef] [PubMed]
58. Urhausen, A.; Kindermann, W. Diagnosis of overtraining: What tools do we have? *Sports Med.* **2002**, *32*, 95–102. [CrossRef] [PubMed]
59. Borges, N.R.; Driller, M.W. Wearable Lactate Threshold Predicting Device is Valid and Reliable in Runners. *J. Strength Cond. Res./Natl. Strength Cond. Assoc.* **2016**, *30*, 2212–2218. [CrossRef] [PubMed]
60. Faude, O.; Kindermann, W.; Meyer, T. Lactate threshold concepts: How valid are they? *Sports Med.* **2009**, *39*, 469–490. [CrossRef] [PubMed]
61. Hayes, L.D.; Bickerstaff, G.F.; Baker, J.S. Interactions of cortisol, testosterone, and resistance training: Influence of circadian rhythms. *Chronobiol. Int.* **2010**, *27*, 675–705. [CrossRef] [PubMed]
62. Brud, L. Amendments to the Laws of the Game—2015/2016 and Information on the Completed Reform of The International Football Association Board. 2015. Available online: http://resources.fifa.com/mm/document/affederation/ifab/02/60/91/38/circular_log_amendments_2015_v1.0_en_neutral.pdf (accessed on 19 February 2017).
63. Gao, W.; Emaminejad, S.; Nyein, H.Y.Y.; Challa, S.; Chen, K.; Peck, A.; Fahad, H.M.; Ota, H.; Shiraki, H.; Kiriya, D.; et al. Fully integrated wearable sensor arrays for multiplexed in situ perspiration analysis. *Nature* **2016**, *529*, 509–514. [CrossRef] [PubMed]
64. Kantoch, E.; Augustyniak, P.; Markiewicz, M.; Prusak, D. Monitoring activities of daily living based on wearable wireless body sensor network. *Conf. Proc. Eng. Med. Biol. Soc.* **2014**, *2014*, 586–589. [CrossRef]
65. Luppa, P.B.; Proll, G.; Imhoff, M.; Koschinsky, T. Analytische Verfahren, Biosensortechnologie. In *POCT-Patientennahe Labordiagnostik*; Springer: New York, NY, USA, 2017; pp. 39–49.

66. Rosenberger, M.E.; Buman, M.P.; Haskell, W.L.; McConnell, M.V.; Carstensen, L.L. Twenty-four Hours of Sleep, Sedentary Behavior, and Physical Activity with Nine Wearable Devices. *Med. Sci. Sports Exerc.* **2016**, *48*, 457–465. [CrossRef] [PubMed]
67. Austen, K. What could derail the wearables revolution? *Nature* **2015**, *525*, 22–24. [CrossRef] [PubMed]
68. Sperlich, B.; Holmberg, H.C. Wearable, yes, but able...?: It is time for evidence-based marketing claims! *Br. J. Sports Med.* **2017**, *51*, 1240. [CrossRef] [PubMed]
69. Düking, P.; Fuss, F.K.; Holmberg, H.C.; Sperlich, B. Recommendations for Assessment of the Reliability, Sensitivity, and Validity of Data Provided by Wearable Sensors Designed for Monitoring Physical Activity. *JMIR mHealth and uHealth* **2018**, *6*, e102. [CrossRef] [PubMed]

Necessary Steps to Accelerate the Integration of Wearable Sensors Into Recreation and Competitive Sports

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Background

A variety of wearable sensor technologies (herein referred to as "wearables") are being developed by an ever-increasing number of companies and receiving considerable attention from the athletic community. Wearables can be defined as small, lightweight devices worn on, close to, or even in the body where they monitor, analyze, transmit, and/or receive data from other devices and/or cloud services to provide biofeedback in real time to the user (1). Wearables can be used by a wide range of individuals engaged in activities of daily living or training and competing as amateur or professional athletes. Wearables may be used to monitor and analyze physiological parameters and individualize training programs to enhance performance and/or health (2–4). Pedometers were among the first wearables developed to measure physical activity by the polymath Leonardo da Vinci some 500 years ago (5). da Vinci's mechanism was designed to measure vertical movements by moving a lever up and down, resulting in the rotation of a gear and this remains the basis of modern day devices. Major advances in technology over the past two decades have resulted in the triaxial accelerometer that measures movements in the anteroposterior, mediolateral, and vertical direction, alleviating the limitations of previous devices (6). Accelerometry-based wearables can be used to objectively assess physical activity and interventions aimed at improving health-related outcomes (7).

In professional rugby union, a device that incorporates Global Navigation Satellite Systems (GNSS), accelerometry, and gyroscope technology is now routinely fitted to the underside of each player's jersey between the shoulder blades. These wearable microsensors allow player movement to be recorded and reported live during match-play, providing team coaches with key performance "metrics" such as total distance covered by a player in match play, number of accelerations and decelerations, and "impact" (8) during any given contact or tackle. It is claimed that these performance metrics enable team coaches to track and plan the match play strategy. Changes in sporting rules and regulations have facilitated the use of these devices. For example, the Competition Rule 144 d of the International Association of Athletics Federations (2018 to 2019) on assistance allows "Heart rate or speed distance monitors or stride sensors or similar devices carried or worn personally by athletes during an event, provided that such device cannot be used to communicate with any other person" (9). Rules such as this promote the use of wearables in elite sport and encourage companies to develop these tools to facilitate high-level performance.

Wearable technology emerged as the top fitness trend in a worldwide survey conducted recently by the American College of Sports Medicine (ACSM) (10), predicting sales of U.S. \$1.5 to U.S. \$2.5 billion for some devices and prompting the statement that "it is unpredictable how wearable technology will advance through the next decade." Advances in wearable innovations are being presented by an increasing number of companies at international wearable technology conferences (*e.g.*, Medical Wearables 2018 (11)). The main marketing claim being low cost and easy-to-use wearables that allow noninvasive or minimally invasive monitoring of a variety of physiological and biomechanical parameters,

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which in the past were simply not possible, or only measurable with sophisticated, time-consuming, and costly laboratory procedures. For example, contact lenses may be used to continuously monitor glucose levels (12), soccer shoes may improve kicking accuracy (13), and fabrics may be commercially available to monitor vital signs such as respiratory rate (14).

Despite the revolutionary potential of wearables, there are well-founded concerns about the wearable industry (15). The main criticisms relate to the lack of evidence for the beneficial effects of analysing a specific parameter in a given context or isolation, the quality of hardware and provided data, information overload, data security, and exaggerated marketing claims (1,15–17). For these reasons, athletes, regulatory bodies, and relevant stakeholders are becoming increasingly sceptical about wearables. The questionable reputation of some wearables is having a detrimental effect on the reputation of evidence-based devices. Aggressive and exaggerated marketing claims and the hasty launch of wearable products with no, or only internal validation and reliability studies, and no external evaluation, are highly problematic (15). Wearable devices that use biological data for health purposes ought to be required to undergo rigorous evaluation before being launched on the market, similar to the process pharmaceutical industries use to test their products (15). Backing up the marketing claims of wearable technology developers with independent scientific evidence would positively impact sports, fitness, and health market. Failure to do so should be subject to financial and other penalties as happened in the past (18,19). Wearable technology that is backed by quality science will be more profitable and sustainable in the long run, and the companies involved will have a much higher return on their investment.

Current Applications

A recent example used in elite sport and associated with the International Federation of Sports Medicine (FIMS) is the mobile application developed by sport scientists and engineers for the Sub2hrs marathon project (20,21). The Sub2hrs project is the first dedicated international multidisciplinary research initiative to include scientists from academia, elite athletes, and strategic industry partners with the aim of running a sub two-hour marathon while promoting doping-free and fair sport. The Sub2 mobile application (Fig. 1) was developed to serve as a "hub" to aggregate a range of data feeds to assist elite runners and their support teams to improve athletic performance. In addition, the "hub" is intended to improve the experience of spectators through real time broadcasting of information pertaining to the "live" performance. This application can provide highly precise real-time measures for athletes and their support teams, such as distance run and speed using a proprietary algorithm. A number of sensors to measure heart rate, running economy, and core temperature along with other physiological and kinematic parameters (*e.g.*, contact time, cadence, strike angle) can be integrated to provide a holistic and comprehensive overview of the activity and its impact on the athlete. The app provides a live data feed of land and air temperature based on geostationary satellite data as well as state-of-the-art machine learning techniques. This is facilitated through a Cloud-based portal allowing the athlete support team to view the data on a desktop, tablet, or a smartphone in real time anywhere around the globe with internet access. The Sub2 mobile application runs on smartwatches with the Android Wear 2.0 operating system and standalone connectivity, overcoming the need for the smart watch to be paired to a smartphone (Fig. 1). Historically, such capacity to transmit biometric data such as body temperature, pace, cadence, heart rate, and breathing rate in real time during a race was only possible using tablets held by nearby cyclists following the runners at all times (22) or by recording singular data points at predetermined distances or times along the course. The app performance was tested on an elite female athlete during the recent Seville marathon (Fig. 2). Physiological and biomechanical parameters were monitored and

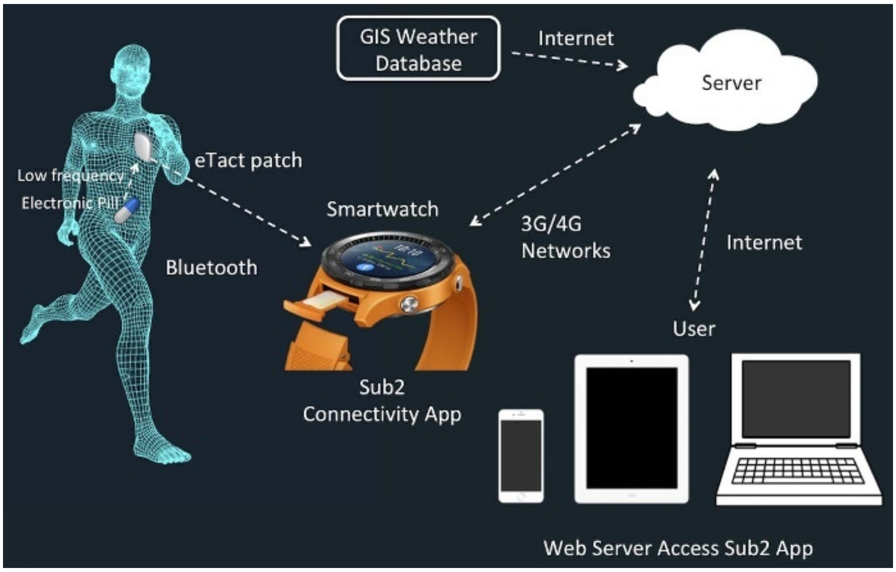

Figure 1: The Sub2 mobile application.

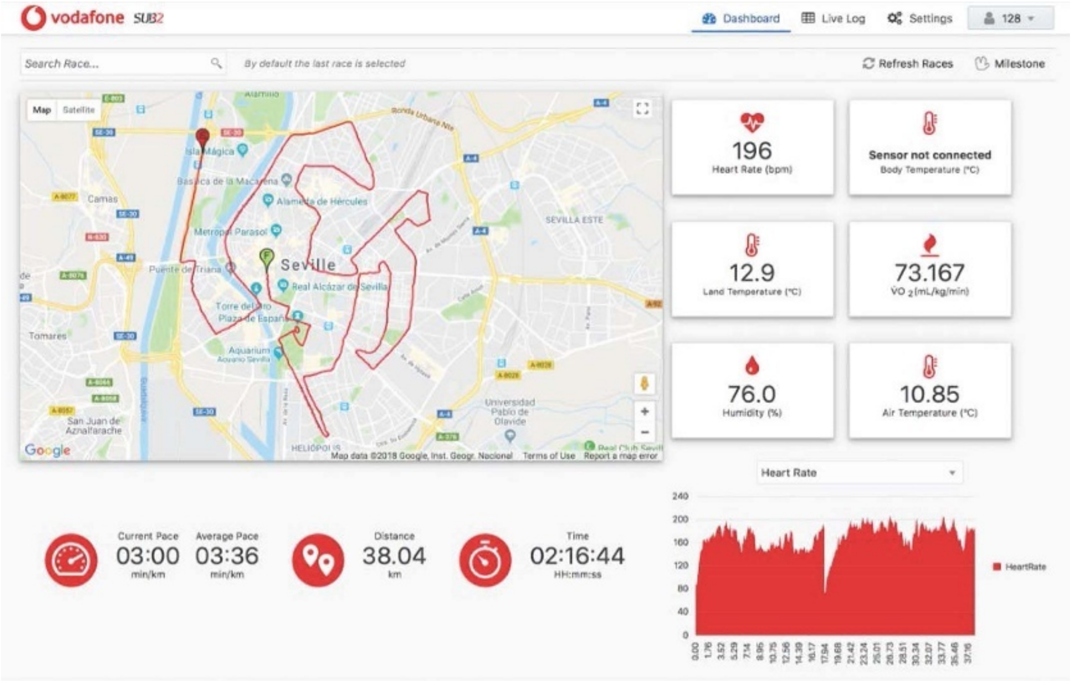

Figure 2: An example of the output during a competitive marathon.

transmitted live to scientific support staff in the United Kingdom, South Korea, and Ethiopia through the Sub2 mobile application.

Daily life is becoming increasingly sedentary, and physical inactivity is a global pandemic. Applications and wearables have great potential as tools to promote and increase the levels of daily physical activity (23). Although the use of this technology is a promising alternative to combat inactivity, the efficacy of this approach remains to be determined. In a recent multidisciplinary review of 111 studies (24), less than one third were optimized for effectiveness, engagement, and acceptability and the review concluded that guidelines were needed to facilitate the synthesis of evidence across disciplines.

Scientific Basis of Wearable Parameters

The potential to measure almost every foreseeable parameter with a wearable device is real. However, not every parameter is practical for either the recreational or competitive athlete (17). Using the prior Rugby Union example, monitoring the covered distance during match play and/or training using GNSS may provide some interesting information but knowing the covered distance *per se* is unlikely to optimize performance and/or reduce the likelihood of injuries. There are increased efforts to understand the relationship between covered distances in different intensity zones and the likelihood of injury (25–28). In this context, it is important not to confuse the association between a parameter (in this case the covered distance) and an outcome (in this case the likelihood of injury) with the predictive power of a parameter as it was shown that despite being associated, parameters are not always good for prediction (29,30).

Research to develop evidence-based algorithms that support the use of specific parameters to predict injuries and potentially aid in injury prevention is needed. It is important to investigate the interaction between monitored parameters and aspects of performance and/or health that wearables may detect. Collaborative efforts between sport practitioners, engineers, data analysts, sports medicine personnel, and other relevant groups will form a science base for the application of this technology. Easy access to raw data from wearable devices would speed advances and benefit the athlete, scientific community, manufacturer, and practitioner. Wearable companies typically work in isolation to safeguard their intellectual property. In the future, if wearable companies are to become more evidence-based in their approach, they will need to develop multidisciplinary teams that place greater value on research and development.

Quality Control

Quality control of the hardware and the data generated is crucial for wearables to improve athlete performance and health. While there are many wearables that claim to deliver reliable and valid data to the user (31,32), few wearables have had rigorous independent testing (1). Independent research institutions should at least test for the validity and reliability of wearable technology before releasing the products on the market (1,33). Recommendations exist for the assessment of reliability, sensitivity, and validity of data provided by wearables (34). Hardware also should be tested to reduce the risk of harm to the user. Third party, independently verified quality assurance, durability (battery life), survivability (water resistance), and data protection would significantly enhance a products reputation and potential use (35,36). Good quality control of the hardware, the safety, and privacy of the data would increase the reliability of the data generated and improve the comparison between devices.

Improving User Interface

Wearables need to be simple and time-efficient for a high level of compliance and usage (33). Monitoring simple subjective data (*e.g.*, ratings of perceived exertion) can be done with a touch interface and advancements in speech and voice recognition allow more complex data to be gathered verbally (37). Collaboration with athletes is needed to determine the most suitable form of instant feedback, that is, what information do they need to know to improve performance while not being distracted from their surroundings. Regardless of the presentation medium (*e.g.*, smartwatch, smartphone, "hearables," etc.), the information needs to be in an informative and easily understandable format (38). This is critical, especially when the slightest distraction may decrease performance in disciplines where concentration is paramount to success (*e.g.*, Formula 1, MotoGP, cycling, and skiing) and participant safety. In the future, biofeedback that is not provided instantly could possibly be provided in a virtual reality environment allowing the athlete to receive the feedback and implement strategies to improve aspects of performance (39). Future studies are needed to evaluate the most useful and suitable form of feedback for different athletic tasks and disciplines and to present the data in an understandable and attractive format (38).

Data Collection and Handling

To enhance high-level performance, a variety of multiple wearables will likely need to be connected to gather the relevant data within a single database for interpretation. Data that are standardized and easy to share will enhance and facilitate collaboration and big data analytics may identify new relationships between the parameters measured, further enhancing sports performance and health (1,40,41). Developing such large databases and the algorithms they may produce will require the collaborative effort of data service providers, exercise scientists, athletes, and data analysts to generate meaningful and useful information. The motivation to use wearables varies between the populations using them. However, if production of the device is not sustainable and the data is not reliable, valid and/or actionable, no one will ever benefit from this technology.

Concluding Remarks

In the future, athletes will have the option to use an increasing number of wearables and each new device should add beneficial information to the training process with the goal of helping sports scientists and health care providers improve their athlete's or patient's performance and/or health. Sharing data and knowledge between the athletes, exercise scientists, hardware and software engineers, and other stakeholders has the potential to improve wearable devices and technology for competitive athletes.

PD is an employee of Wearable Technologies AG which is active in consulting to companies and in hosting events specific to the wearable market. CS is the CEO of Wearable Technologies AG. YP is the founding member of the Sub2 project.

References

1. Düking P, Hotho A, Holmberg HC, *et al*. Comparison of non-invasive individual monitoring of the training and health of athletes with commercially available wearable technologies. *Front. Physiol.* 2016; 7:71.
2. Brud L. Amendments to the Laws of the Game—2015/2016 and information on the completed reform of The International Football Association Board. 2015 [cited 2018 Feb 19]. Available from: http://resources.fifa.com/mm/document/affederation/ifab/02/60/91/38/circular_log_amendments_2015_v1.0_en_neutral.pdf.
3. Düking P, Holmberg HC, Sperlich B. Instant biofeedback provided by wearable sensor technology can help to optimize exercise and prevent injury and overuse. *Front. Physiol.* 2017; 8:167.
4. Baas J. Use digitization to promote health and the solidarity community. [cited 2017 Nov 5]. Available from: http://www.webcitation.org/query?url=https%3A%2F%2Fwww.tk.de%2Ftk%2Fthemen%2Fdigitale-gesundheit%2Fgesundheitsfoederung-durch-fitnesstracker-interview-dr-jens-baas%2F931248&date=2017-11-05.
5. Montoye HJ. Measuring physical activity and energy expenditure. *J. Hum. Kinet.* 1996:3–118.
6. Plasqui G, Westerterp KR. Physical activity assessment with accelerometers: an evaluation against doubly labeled water. *Obesity (Silver Spring)*. 2007; 15:2371–9.
7. Ojiambo R, Konstabel K, Veidebaum T, *et al*. Validity of hip-mounted uniaxial accelerometry with heart-rate monitoring vs. triaxial accelerometry in the assessment of free-living energy expenditure in young children: the IDEFICS Validation Study. *J. Appl. Physiol. (1985)*. 2012; 113:1530–6.
8. Gabbett TJ. Quantifying the physical demands of collision sports: does microsensor technology measure what it claims to measure? *J. Strength Cond. Res.* 2013; 27:2319–22.
9. IAAF Competition Rules 2018–2019, 144 (2017).
10. Thompson W. Worldwide survey of fitness trends for 2017. *ACSM's Health Fit J.* 2016; 20:8–17.
11. Medical Wearables, 3rd Annual Conference and Exhibition. 3rd Annual Conference and Exhibition; 2018. Santa Clara, California: Medical Wearables, 2018.
12. Ascaso FJ, Huerva V. Noninvasive continuous monitoring of tear glucose using glucose-sensing contact lenses. *Optom. Vis. Sci.* 2016; 93:426–34.
13. Fuss FK, Düking P, Weizman Y. Discovery of a sweet spot on the foot with a smart wearable soccer boot sensor that maximizes the chances of scoring a curved kick in soccer. *Front. Physiol.* 2018; 9:63.
14. Lo Presti D, Massaroni C, Saccomandi P, Caponero MA, *et al*. A wearable textile for respiratory monitoring: feasibility assessment and analysis of sensors position on system response. Conf. Proc. *IEEE Eng. Med. Biol. Soc.* 2017:4423–6.
15. Sperlich B, Holmberg HC. Wearable, yes, but able…?: it is time for evidence-based marketing claims! *Br. J. Sports Med.* 2017; 51:1240.
16. Halson SL, Peake JM, Sullivan JP. Wearable technology for athletes: information overload and pseudoscience? *Int. J. Sports Physiol. Perform.* 2016; 11(6):705–6.
17. Meyer T. How much scientific diagnostics for high-performance football? *Sci. Med. Football*. 2017; 1:95.
18. Federal Trade Comission. Reebok to Pay $25 Million in Customer Refunds to Settle FTC Charges of Deceptive Advertising of EasyTone and RunTone Shoes. Federal Trade Commission; 2011 [cited 2018 Feb 19]. Available from: https://www.ftc.gov/news-events/press-releases/2011/09/reebok-pay-25-million-customer-refunds-settle-ftc-charges.
19. Christensen CJ. Fitbit accuracy questioned in lawsuit. CNN; 2018; [cited 2018 Feb 19]. Available from: https://www.cnn.com/2016/05/20/health/fitbit-accuracy-questioned/index.html.
20. Group V. Vodafone joins attempt to break two hour marathon barrier. Vodafone; 2017; [cited 2018 Feb 19]. Available from: http://www.vodafone.com/content/index/what/technology-blog/sub2.html.
21. Pitsiladis Y, Ferriani I, Geistlinger M, *et al*. A holistic antidoping approach for a fairer future for sport. *Curr. Sports Med. Rep.* 2017;16:222–4.
22. Range of runners will supply biometric data for marathon's TV broadcast. Sports Business Journal; 2016. Available from: https://www.sportsbusinessdaily.com/Journal/Issues/2016/10/31/Marketing-and-Sponsorship/NYC-Marathon-biometrics.aspx.
23. Simons D, De Bourdeaudhuij I, Clarys P, *et al*. A smartphone app to promote an active lifestyle in lower-educated working young adults: development, usability, acceptability, and feasibility study. *JMIR Mhealth Uhealth*. 2018; 6:e44.
24. McCallum C, Rooksby J, Gray CM. Evaluating the impact of physical activity apps and wearables: Interdisciplinary review. *JMIR mHealth uHealth*. 2018; 6:e58.
25. Chambers R, Gabbett TJ, Cole MH, Beard A. The use of wearable microsensors to quantify sport-specific movements. *Sports Med.* 2015; 45:1065–81.
26. Li RT, Kling SR, Salata MJ, *et al*. Wearable performance devices in sports medicine. *Sports Health*. 2016; 74–8.

27. Gabbett TJ, Ullah S. Relationship between running loads and soft-tissue injury in elite team sport athletes. *J. Strength Cond. Res.* 2012; 26:953–60.

28. Gabbett TJ. The training-injury prevention paradox: should athletes be training smarter and harder? *Br. J. Sports Med.* 2016; 50:273–80.

29. Bahr R. Why screening tests to predict injury do not work-and probably never will…: a critical review. *Br. J. Sports Med.* 2016; 50:776–80.

30. Fanchini M, Rampinini E, Riggio M, *et al.* Despite association, the acute: chronic work load ratio does not predict non-contact injury in elite footballers. *Sci. Med. Football.* 2018:1–7.

31. Giles D, Draper N, Neil W. Validity of the Polar V800 heart rate monitor to measure RR intervals at rest. *Eur. J. Appl. Physiol.* 2016; 116:563–71.

32. Roe G, Darrall-Jones J, Black C, *et al.* Validity of 10 HZ GPS and timing gates for assessing maximum velocity in professional rugby union players. *Int. J. Sports Physiol. Perform.* 2016; 13:1–14.

33. Starling LT, Lambert MI. Monitoring rugby players for fitness and fatigue: what do coaches want? *Int. J. Sports Physiol. Perform.* 2017; 15:1–30.

34. Düking P, Fuss F, Holmberg H, Sperlich B. Recommendations for assessment of the reliability, sensitivity and validity of data provided by wearable sensors designed for monitoring physical activit. *JMIR Mhealth Uhealth*. 2018; 6:e102.

35. Kang THaC. Demands grow for Facebook to explain its privacy policies. 2018;20180326.

36. Sued T. Certification mark for fitness trackers. [cited 2018 March 14]. Available from: https://www.tuev-sued.de/product-testing/certificates/certification-mark-for-fitness-trackers.

37. MarketsandMarkets. Speech and Voice Recognition Market by Technology (Speech Recognition, Voice Recognition), Vertical (Automotive, Consumer, Banking, Financial Services and Insurance (BFSI), Retail, Education, Healthcare & Government) and Geography - Global Forecast to 2023. 2017. Available from: https://www.marketsandmarkets.com/Market-Reports/speech-voice-recognition-market-202401714.html.

38. Buchheit M. Want to see my report, coach. Sport science reporting in the real world aspetar. *Sports Med. J.* 2017; 6:36–42.

39. Düking P, Holmberg HC, Sperlich B. The potential usefulness of virtual reality systems for athletes: a short SWOT analysis. *Front. Physiol.* 2018; 9:128.

40. Halson SL. Monitoring training load to understand fatigue in athletes. *Sports Med.* 2014; 44(Suppl 2):S139–47.

41. Sperlich B, Holmberg HC. The responses of elite athletes to exercise: an all-day, 24-h integrative view is required! *Front. Physiol.* 2017; 8:564.