Northumbria Research Link

Maturitas 113 (2018) 40–47

Contents lists available at ScienceDirect

Maturitas

journal homepage: www.elsevier.com/locate/maturitas

From A to Z: Wearable technology explained

A. Godfrey[a,*], V. Hetherington[b,c], H. Shum[a], P. Bonato[d], N.H. Lovell[e], S. Stuart[f]

[a] Department of Computer and Information Science, Northumbria University, Newcastle upon Tyne, NE2 1XE, UK
[b] NIHR Clinical Research Network, Wolfson Research Centre, Campus for Ageing and Vitality, Newcastle upon Tyne, UK
[c] Northumberland Tyne and Wear NHS Foundation Trust, Wolfson Research Centre, Campus for Ageing and Vitality, Newcastle upon Tyne, UK
[d] Department of Physical Medicine & Rehabilitation, Spaulding Rehabilitation Hospital, Harvard Medical School, USA
[e] Graduate School of Biomedical Engineering, UNSW Sydney, Australia
[f] Department of Neurology, Oregon Health and Science University, Portland, OR, USA

ARTICLE INFO

Keywords:
Analysis
Data
Gadget
Healthcare
Informatics
Internet of Things (IoT)
Wearable technology

ABSTRACT

Wearable technology (WT) has become a viable means to provide low-cost clinically sensitive data for more informed patient assessment. The benefit of WT seems obvious: small, worn discreetly in any environment, personalised data and possible integration into communication networks, facilitating remote monitoring. Yet, WT remains poorly understood and technology innovation often exceeds pragmatic clinical demand and use. Here, we provide an overview of the common challenges facing WT if it is to transition from novel gadget to an efficient, valid and reliable clinical tool for modern medicine. For simplicity, an A–Z guide is presented, focusing on key terms, aiming to provide a grounded and broad understanding of current WT developments in healthcare.

1. Introduction

Wearable technology (WT, or wearable computing) encapsulates a plethora of devices worn directly on or loosely attached to a person. Commonly, the latter comprises smartphones, which have become integral to the popularity and functionality of WT [1]. Although there is a debate defining smartphones as WT, their existence has seen the demise and rebirth of WT as useful aids to assist daily living [2]. This is primarily due to the rise of third party applications (i.e. apps) which have nurtured innovation but at the expense of well-organised app development, leaving the end-user overwhelmed with choices. Indeed, the mobile computing power of smartphones is so influential that they will likely play a key role in ongoing WT innovations such as performing quick, robust and easy bioassays anywhere and at any time [3].

In short, WT can be subdivided into two categories: (i) primary, those operating independently and functioning as central connectors for other devices and/or information (e.g. wrist worn fitness tracker, smartphone) and; (ii) secondary, capturing specific actions or executing a measurement (e.g. heart rate monitor worn around the chest) offloading to a primary wearable device for analysis [4]. Additionally, those categories may include smart textiles where the physical properties of the material can measure or react to stimuli from the user or environment [2]. Smart textiles currently lay beyond the scope of normal daily use as the concept of wearing electronic or uncommon tailoring materials interwoven within clothes or directly on the skin remains the vernacular of technological idealists.

Nevertheless, fuelled by miniaturisation of electronic-based components, WT has experienced an evolution since first appearing as means to take traditional desktop computing on the go [1]. With the ability to gather and store data as well as perform complex permutations in any real-world environment it hasn't taken WT long to enter the healthcare domain, recognised as useful tools to aid patient assessment, treatment and management. Yet, the true utility of current WT (and associated communication infrastructures) remains lacking with development of novel WT usually exceeding pragmatic (clinical) use. Regulatory bodies and vendors hamper clinical adoption, struggling to differentiate between apps classified as medical devices requiring formal regulatory approval, versus wellness apps for general use by the consumer market. Qualification of device efficacy and safety, adoption of various standards for accurate analysis and device and communications interoperability are all interwoven, presenting further barriers to clinical adoption of WT. There is also a dearth of knowledge pertaining to the fundamentals of WT, e.g. outcomes generated and relevance to specific pathologies; suitable WT selection; appropriate data management and analysis. The aim of this review is to highlight key aspects of WT for those less familiar with their robust application in healthcare. Currently, there is a myriad of technologies and terminologies overwhelming those less familiar with this field. Here, we provide a concise overview for those aiming to familiarise themselves with WT.

* Corresponding author.
E-mail address: alan.godfrey@northumbria.ac.uk (A. Godfrey).

https://doi.org/10.1016/j.maturitas.2018.04.012
Received 5 April 2018; Accepted 24 April 2018

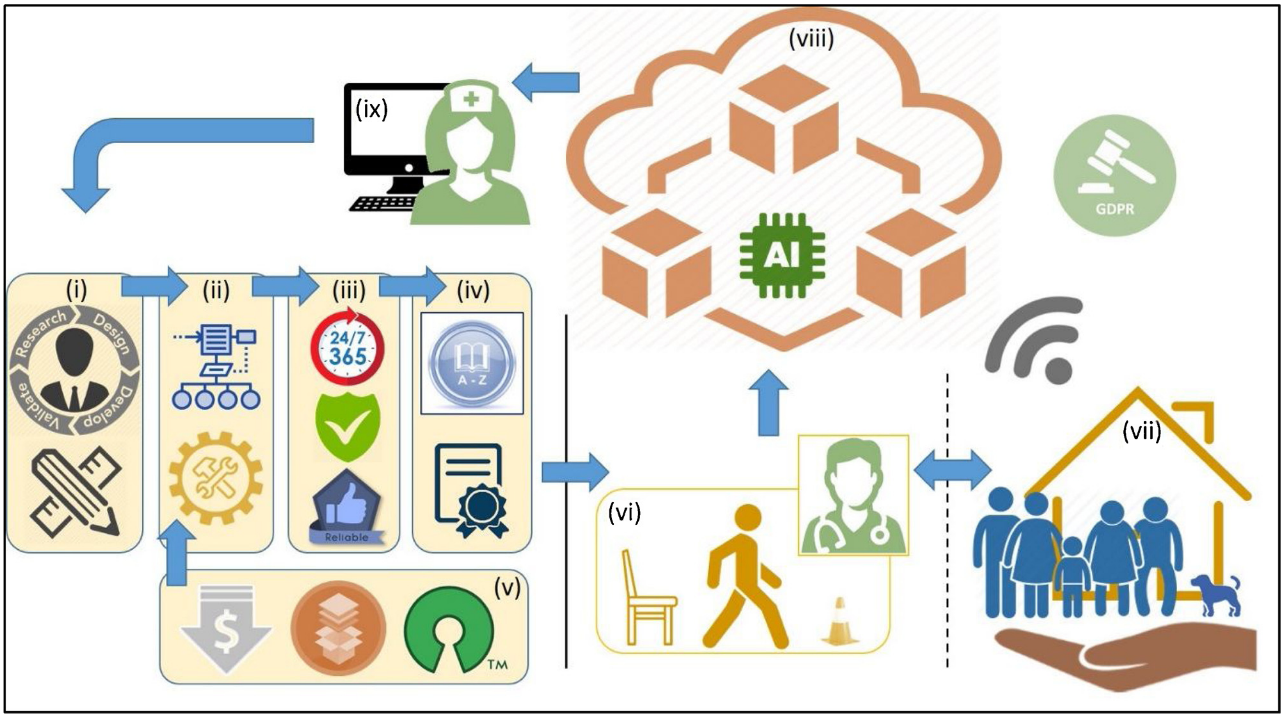

Fig. 1. A simplistic overview of the A–Z of wearables. (i, top-to-bottom) Co-creation with adults of all ages is paramount to the successful design of WT for continued daily use, influencing how WT is worn (ii) this will impact algorithm and hardware designs on how best to capture physiological measurements, (iii) once created WT will need to be efficient, valid/verified and reliable to robustly capture outcomes for longitudinal periods, (iv) adoption is simplified by translational/transparent terminology and implementing an expert consensus of standards, (v, left-to-right) the use of low cost technology including development kits and open source can facilitate novel and streamlined WT development, (vi) valid and reliable WT can better facilitate supervised patient assessment during instrumented testing in generic environments with more sensitive electronic-based data, (vii) WT (e.g. jewellery) can also provide habitual data on a range of generations facilitating self-care, (viii) WT connectivity to cloud computing, adhering to strict GDPR regulations, ensures ubiquitous sensing capabilities where embedded machine learning or artificial intelligence systems can decipher meaning from big data, (ix) WT data on the cloud can be accessed by healthcare professionals from any browser, facilitating ease of patient care. Feedback/involvement from those in the health services (or patient) should be used to inform design processes.

2. Wearables: an A–Z guide

The following details a selection of the most commonly used devices, terminologies and areas of interest. For simplicity, we present an *A–Z* guide (Fig. 1).

2.1. A is for algorithm

WT comprise different electronic-based sensors depending on measurement needs, e.g. electrocardiogram, blood glucose. For simplicity, sensors will generate an electrical signal when detecting physiological signs/responses, captured many times a second (high sampling frequency, SF) or every few minutes (low SF) depending on measurement needs. Subsequently, signals are stored as complex/raw time series data by acquisition electronics. Off-the-shelf commercial devices use proprietary software with embedded algorithms to download data, extract pertinent features and generate required outcomes (e.g. heart rate). Additionally, most WT facilitate access to raw data to allow the creation of bespoke algorithms via research tools (e.g. Matlab®, R) for more insightful patient assessment [5]. This aligns to trends in *open-source* development options, making algorithms transparent compared to black-box designs. Broadly, algorithms (within software/apps) are structured computer-based protocols to process and analyse sections of raw electronic signals/data to derive real world, meaningful outcomes. Algorithm syntax can be complex given the permutations of data interpretation needed but pseudo-code representations offer some insight to operations, like in eye tracking [6].

2.2. B is for big data

WT can continuously monitor many times a second for days or weeks. However, this will negatively affect running time between battery recharge/replacement and memory capabilities: increased data capture means reduced WT deployment time. Although WT can use large batteries or memory units, this will make WT impractical, too big and bulky to wear discretely. Thus, when deploying WT, data acquisition appreciation is required to ensure robust data collection procedures. For example; too little data and vital clues to diagnose or treat a patient may be missed; alternatively, mining/searching big data for clinically sensitive/relevant outcomes is complex. One common approach is to place WT in a low-power mode and only power up additional sensors when a possible event that is of interest has been detected [7]. Big data collected in free-living environments can offer insight to habitual behaviours such as seasonal trends, normally lacking under direct typically episodic clinical observation [8]. Yet, many obstacles exist for mainstream use of big data within healthcare such as choosing optimal architecture for storage (e.g. Structured Query Language, SQL) and analytical system (e.g. Apache HIVE), where one size does not fit all [9].

2.3. C is for cloud (computing)

Most WT is now part of the Internet of Things (IoT): connectable to digital communication infrastructures, facilitating rapid data transmission and storage. The latter is big business and growing, with overwhelming future estimates of 2.3 trillion gigabytes (GB) of IoT-based data produced daily by 2020 [10], reaching an accumulation of

847 zettabytes[1] (ZB) by 2021 [11]. Indeed, we are on the cusp of the yottabyte (YB) era[2] which heralds a need to consider how big data is used as large proportions remain underutilised [11]. The cloud (and clustered IT infrastructures, i.e. data centres) can overcome limitations by providing ubiquitous computerised economies of scale: the power of a super computer accessed anywhere through any device. However, cloud computing is still maturing, such as implementing optimisation methodologies like (the aptly named) fogs and cloudlets to process data at network edges, i.e. on more local systems like smartphones. Hence, that topic of research is termed *edge computing* where real-time analytics plays a key driver to improve data efficiency [12].

2.4. D is for design

Technology-driven developments rather than co-creation driven by end-users (user centred design) led to discrepancies between project aims and outputs from the EU Ambient and Assisted Living Joint Programme [13]. Although WT stems from an evolution of computing and sensing technologies, its continued revolution relies on interactions with numerous stakeholders from all ages. Younger generations[3] are exposed to technologies from an early age, making adoption and use instinctual. Yet, older adults remain excluded from aiding technology design and development for their generation, described as a lack of involvement to build their (own) future [14]. Furthermore, WT often lacks considerations for the wearer's physical, psychological and social preferences [15] as holistic end-user preferences need consideration [16]. Contemporary frameworks exist to guide WT design ensuring a human-centred approach [16], as well as novel reflective themes which could be more broadly applied to other topics influencing WT [14].

2.5. E is for efficiency

Deploying WT for prolonged periods is difficult due to two primary WT criteria: battery life and memory capacity. Current studies aiming to gather longitudinal data may adopt a series of n-of-1 methods, repeated measurement of an individual over time (with low SF) allowing conclusions to be drawn about the individual [17]. That method of data gathering can complement traditional study designs and would help personalise health behaviour interventions to individuals [18]. Moreover, it could help carefully manage study resources, optimising personnel time and minimise costs due to reduced WT expenditure. However, studies needing to deploy WT on larger patient numbers for more data (with high SF) must deal with device logistics, e.g. rotating fully charged WT between users. Typically, battery limitations outweigh memory, as it constitutes the bulkiest component. Alternatively, energy harvesting for improved efficiency, utilises the dynamic energy (e.g. body heat, friction, movement) of the wearer to continuously (months) power wearables through smart materials has been suggested [19].

2.6. F is for fusion

Current WT inefficiencies are offset by the application of data fusion techniques from different sensors and technologies. For example, a more reliable indication of pulse rate is achievable by signal fusion from electrocardiogram and pulse oximetry. Continuous monitoring with WT is aided by gathering additional data from ubiquitous devices placed within habitual environments. Yet, coherent analysis with data gathered from other sensor types, capturing at diverse specifications with alternate algorithms, is a challenge. Data fusion techniques stemming from WT have been presented [20], detailing considerations like number of sensors to adequately provide seamless monitoring, paramount for complex conditions with multiple co-morbidities. Multi-sensor data fusion has many engineering obstacles [21], but pragmatic implementation remains equally challenging, e.g. access to commercial data; knowledge sharing between companies; uptake/integration within national/private health services.

2.7. G is for GDPR (General Data Protection Regulation)

In 2016 the EU Parliament approved GDPR to replace the Data Protection Directive 95/46/EC, aiming to empower individuals by strengthening and merging data protection as well as addressing the export of personal data outside the EU[4] (Additional information found here[5]). Requirements for firmer data regulations were justified by considering technology foresight and examining a range of national and political organisations influencing policy across many technologies [22]. Four factors were identified which complicate data protection and privacy that are applicable to WT:

1. It's hard to understand what new technologies are doing and the real limits of their capabilities.
2. Technological development is not linear and disruptive breaks can occur which bring about qualitative changes in circumstances, making prediction from past technologies challenging.
3. Technology cannot be taken in isolation; it should be assessed alongside a range of other technologies to aid combination.
4. Technologies do have affordances (relational properties supporting different actions) but can be used in ways unintended by designers and developers.

A notable example of the latter was a serious security breach of wrist worn WT in the context of divulging secret information (i.e. key entries) while people accessed key-based security systems [23].

2.8. H is for hardware

Most WT may comprise the same underlying hardware, the only difference being algorithms and visualisation tools (on a smartphone/computer) that decipher and graph the data, respectively. One example is WT quantifying human movement, where inertial sensors (typically accelerometers) generate a signal when the wearer moves. Depending on where WTs are worn, sensors will generate different signal shapes requiring different algorithms to interpret data to generate specific outcomes [24]. Generally, more outcomes mean more embedded sensors or algorithm complexity creating a trade-off for length of use, influenced by: (i) battery life (to power all functionality) and; (ii) abundance of data stored.

2.9. I is for instrumented

WT value in everyday clinical practice is yet to be realised. WT is often used without healthcare professionals appreciating the extent of its capabilities but broad recommendations are provided [25]. Furthermore, WT can be a hindrance to those in working in healthcare due to cost, complexity of integration to existing technology frameworks and need to upskill. Sometimes *low-tech* works but realising how WT can add value is key. Recent approaches to understanding ageing phenotypes highlight the instrumented approach to measure traditional tasks like gait speed, replacing manual observations with a stopwatch. Where the latter was prone to observation variations/errors in recording(s), WT facilitates a standardised (computerised) approach to

[1] 1 ZB = 1000^7 bytes = 10^{21} bytes = 1,000,000,000,000,000,000,000 bytes = 1000 exabytes (EB) = 1 million petabytes (PB) = 1 billion terabytes (TB) = 1 trillion GB.

[2] 1 YB = 1000^8 bytes = 10^{24} bytes = 1,000,000,000,000,000,000,000,000 bytes = 1000 ZB = 1 trillion TB.

[3] Those collectively labelled generations: Z, Y (millennials) and less often, X.

[4] www.eugdpr.org.

[5] Information Commissioners Office: ico.org.uk/for-organisations/resources-and-support/getting-ready-for-the-gdpr-resources.

Table 1
Recent smart jewellery examples (www.smartgeekwrist.com/best-smart-jewelry).

Name	Worn	Health-based functionality	Colour
Bellabeat Leaf Urban	Neck, wrist, clip	Activity and sleep, Stress, Menstrual cycle	Rose Gold, Silver
Ringly Luxe smart ring	Fingers	Activity tracking (steps, distance, calories burned). Mindfulness – meditation and breathing exercises	Gold/Lapis, Gold/Black Onyx
Fitbit Flex 2	Wrist	Activity (including swimming) and sleep tracking	Black, Lavender, Magenta, Navy
Misfit Shine (with Bloom Necklace)	Wrist, neck	Activity (inc. sports) and sleep tracking.	Black, Grey, Champagne and 7 more
Ringly Luxe smart bracelet	Wrist	Activities (steps, distance, calories burned)	Silver/Blue Lace Agate, Gold/Lapis
Omate Ungaro	Finger	None – vibration alerts for calls and texts	Gold, Silver
Michael Kors access bracelet	Wrist	Activity tracker with sleep monitoring	Rose Gold/Pink, Black, Blue, Silver, Rose Gold/Grey
Mira wellness & activity bracelet	Wrist, clip	Activities (steps, elevation, calories burned, distance). Motivation (gives fitness tips)	Midnight Purple
Joule earring backing	Earring backing	Continuous heart rate tracking. Activity tracking and level measurement	Silver
Netatmo June	Bracelet	UV bracelet hat's designed to keep you safe from the sun's harmful rays	Gold, charcoal, platinum
Moodmetric	Ring	Stress management (detects stress levels by measuring electrodermal activity)	Black, grey, plum and turquoise
Grace	Wristband (bracelet)	Automated tracking and cooling device for women experiencing menopausal hot flushes	Rose gold with grey

gathering data in any environment, often with additional outcomes usually obtained by larger and more expensive devices in specialist settings [26,27]. Additionally, ongoing work is examining motor phenotyping individuals (e.g. Parkinson's and Alzheimer's disease), where WT has gained a great deal of interest among rehabilitation and movement disorder specialists [28,29].

2.10. J is for jewellery

A recent exploration of patents suggested that a key factor for immediate WT success is a need for a clear strategic vision within healthcare [30]. The referenced study suggests that in addition to focusing on current WT norms (e.g. smartwatch) companies should invest in new subclasses (e.g. smart jewellery) where there are high potentials for growing products. Suggestions by a major telecommunications services provider propose sensors beneath the skin as mainstream by 2049 to aid automated emergency responses. Current work to achieve that goal is examining mobile (false) nails accompanied by connected jewellery that will let you talk into the nail by raising your finger to your face [31]. Although that idea is visionary and stylish, current WT jewellery (Table 1) are equally so but lack focus and the "wow" factor [32] by replicating mundane outcomes: there is a need to merge style with leading research to ensure novel concepts aren't left in the vintage collection.

2.11. K is for kits

Professional groups no longer work in isolation; there is a requirement for multidisciplinary teams to share experiences and knowledge. Therefore, the necessity to be technology literate is more profound than ever allowing diverse groups to work efficiently and effectively. For those within healthcare sciences, developer kits (DK) are presented as a means of increasing some basic technical insights to WT. Typically, software DK (SDK) are more commonly discussed (e.g. SDK[6] for an iOS app) but they are quite complex and require specific expertise. Alternatively, affordable hobby-based DK are growing in popularity. Generally, DK come with simple projects for hardware and software integration as well as online help resources. Current DK allow easy upskilling and a basic appreciate of some technical WT design and development, Table 2.

2.12. L is for low cost

WT offers a *one-stop-shop* to monitor people in their natural living environments, potentially offering better insight compared to occasional clinical observations. A single WT can offer numerous sensing capabilities with multiple algorithms, termed collapse of functionality [33], to allow for more streamlined and efficient healthcare monitoring. Commercial competition and huge economies of scale drive the price of WT down, passing low costs to the consumer (single user or health service provider). The ability to self-monitor (e.g.) to avoid the burden of waiting rooms has led consumers (patients) yearning for convenience, simplicity, speed and immediate satisfaction. Consequently, there is increasing growth for affordable on-demand services (e.g. Uber) where health represents the second fastest growing segment [34].

2.13. M is for machine learning

Machine learning (ML, akin to computational statistics) algorithms have emerged as useful analytical methodologies, undoubtedly due to the rise of big data. Typically, the machine/computer learns from a training set of data where outcomes are mapped to specific data characteristics. That is the basic concept that differentiates ML from artificial intelligence (AI), the latter being more autonomous. ML is captured for clinical scientists in a previous tutorial including: relevant terminology; relationship to traditional biomedical statistics; application to WT clinical measurement[7]; and limitations [35]. ML algorithms and their application(s) are numerous, current examples include: decision trees for classifying motoric activities [36]; and neural or deep learning networks for measuring upper limb rehabilitation [37], disease state in Parkinson's [38] and managing large amounts of time series data from a large number of input channels with a high temporal resolution (several kHz) such as electroencephalography [39]. Table 3 describes an open resource for those wishing to try some ML-based analysis.

2.14. N is for nursing

An article published before the turn of the millennium highlighted a dilemma for healthcare workers (i.e. nurses): slaves or masters of technology [41]. The article provided several guidelines (some equally as relevant today for WT) to help frontline staff carefully assess the impact of emerging technologies (Table 4). Of paramount importance

[6] https://developer.apple.com/ios.

[7] In Parkinson's disease.

Table 2
Hobby-based developer kits for educational purposes.

Company/kit name	Features	Useful information	Getting started
Inxus/Verve2	New device featuring three systems: processing, web data server and data acquisition in a n	Sound, touch (skin), light, temperature, motion, magnetic, buttons to gather basic sensing data	Design and build custom monitoring solutions, data can be saved as CSV files for various analysis
http://myinxus.com/welcome/verve2all/#guide			
Kinoma/Kinoma Create	Create is an integrated Wi-Fi, low-energy Bluetooth, touchscreen, speaker, and microphone	Additional sensors can be purchased from an open-source hardware company (adafruit[a]) to create many projects	Range of online tutorials and projects with supporting code and documentation
http://kinoma.com			
Raspberry Pi	A large community now surrounds this brand aimed at promoting basic computer science.	The brand supports many accessories that can be integrated to create complex sensing solutions	A range of projects and tutorials are available via its website
www.raspberrypi.org			
Arduino	Like Pi, another popular low-cost brand for rapid prototype development	Arduino offers a web editor as well as downloadable software. The former allows you to code anywhere on the go.	An extensive library with built-in examples and tutorials exist to help start development
www.arduino.cc			

[a] www.adafruit.com.

Table 3
Try me – A resource to deploy some ML methodologies.

Waikato Environment for Knowledge Analysis[a]
A Java-based ML software that is openly available.[b] Contains online documentation, video tutorials and courses available through its webpage to explore how it can be used for data mining.
WEKA allows users to dabble with ML algorithms on WT datasets without writing any code. Users access a selection of graphical interfaces, choosing menu and form filling options to implement ML algorithms and visualise the results.
Suggested ways of using WEKA are (i) to apply a ML method to a dataset and analyse its output to learn more about the data or (ii) to use ML models to generate predictions on new instances [40].

[a] www.cs.waikato.ac.nz/ml/weka.
[b] GNU General Public License.

Table 4
1999 based guidelines for wise technology integration.

1. Technology systems must be patient centred
2. Technology must be thoughtfully applied
3. Technology should have an invisible interface when possible
4. Technology should be carefully integrated
5. Nurses must avoid on overreliance on technology
6. Technology must be evaluated as a team
7. Sometimes less is best
8. Technology cannot replace humanity

for point 5 is the authors note that “data are not information” and “must be interpreted before they can be considered real information”. Certainly, the role of current and future WT should enhance the role of frontline staff. Yet, future work must help frontline clinical staff understand how WT data translates to sensitive clinical information/outcomes and how validation and standardisation procedures play a key role in that process.

2.15. O is for open-source

2018 marks the 20th anniversary of the Open Source Initiative[8] (OSI), a non-profit organisation advocating open-source software. For simplicity, (free and) open-sourced software (FOSS) will be described here as software that is freely available and applied as the users deems necessary. There is no doubting OSI and FOSS have proliferated WT research and development (R&D) with languages (e.g. Python™) and platforms (e.g. WEKA, see *W*) accessible to all rather than groups using bespoke software in premier institutes. Open-source (but not necessarily free) hardware examples include Arduino and Raspberry Pi, where the latter slightly differs due to its closed firmware, i.e. low-level software to control specific hardware functionality. Regardless, their low-cost and easy availability make for interesting low-cost solutions to current clinical-based WT research [42].

[8] https://opensource.org.

2.16. P is for pets

WT isn’t just for humans, it has extended its reach to our home-based pets to impact human health. Options exist for pet owners to track the activity of their furry friends in their natural surroundings where some algorithms provide insight to emotional behaviour and stress [43]. In fact, pilot work involving WT showed promise to improve communication between working (guide) dogs and their handlers [44]. Currently, the focus of WT is generally on pet health and costs associated with insurance [45]. However, WT could better inform animal-assisted interventions (AAI) where several theoretical and practical challenges remain [46]. Better understanding of animal and owner activities could aid AAI where dog ownership indicates potential health improvements due to increased ambulation [47].

2.17. Q is for quality of life

WT was recently labelled as a digital compass to navigate everyday choice, counting and controlling how “bites, sips, steps and minutes of sleep” impact health, but this can bypass individual responsibility and self-regulation [48]. Undoubtedly, WT can help users achieve healthier lifestyle goals if regulated with appropriate, expert guidance but over reliance on the fixed thresholds/scores within WT can negatively impact health. Use of wrist-worn WT with feedback mechanisms showed healthier trends in eating and exercise but users felt under pressure to reach daily targets. Almost one third felt the WT was an enemy and made them feel guilty [49]. Therefore, it is important to consider the long-term psychological as well as physiological effects of WT.

2.18. R is for reliability

WT should be validated according to an expert set of standardised validation procedures while also ensuring it remains reliable over time. WT sensors are prone to a phenomenon called *drift*, physical changes which results in error accumulation. Most modern WT should have re-calibration strategies to account for drift, e.g. time synchronisation to network protocols. The use of a *gold standard* reference is often described but in truth, all equipment will slightly differ in their functionality as well as having some inherent error. Therefore, allowance must be made for some discrepancies when comparing between WT and other devices [50]. For those that are unsure, simple *bench testing* of the device against a reliable scale would help check accuracy over time. For example, video recording and counting the steps from a pedometer with a participant on a treadmill at different speeds. Ultimately, calibration procedures must be conducted prior to deployment ensuring (with some confidence) WT reliability.

2.19. S is for standardisation

Technical/engineering standards allow WT to connect via known communication protocols (e.g. Bluetooth) created by the IEC,[9] IEEE[10] or ISO.[11] This allows WT developers to ensure their devices integrate with other technologies. Additionally, some IEEE standards are available which relate to WT measurement, validation and data reporting. An example includes wearable, cuff-less blood pressure measuring devices detailing appropriate statistical analysis that should be taken, ensuring confidence in reported outcomes [51]. However, researchers generally rely on openly available resources to guide work. Contrasting examples include the MapReduce framework for processing and generating big data or the PRISMA[12] set of items in systematic reviews and meta-analyses. Additionally, the Personal Connected Health (PCH) Alliance publishes the Continua Design Guidelines, an implementation framework for authentic, end-to-end interoperability of personal connected health devices and systems. Yet there is scope for standard enhancement with open guidance for non-experts needed on how best to (e.g.) construct algorithms, plan and conduct appropriate validation/reliability protocols as well as statistical analysis.

2.20. T is for terminology

Lack of WT standardisation is encapsulated by heterogeneity of WT terms, with authors often interchanging phrases (e.g. measurement unit, wearable/motion sensors) or creating study specific acronyms that can be confusing for those new to the field. This also relates to similar WT outcomes with notable differences observed. Ideally, the field should be adopting terminology from a predefined set of standards akin to the adoption of clinical terminology created by healthcare specialists.[13] The rationale to do so ensures routine integration of information systems, such as transforming paper into digital records and ensuring universal interoperability among all forms of electronic data.[14] This is of upmost importance when considering (e.g.) file formats, naming conventions or metadata where no common terminology exists although interfacing through the HL7/FIHR would facilitate a useful starting point.[15]

2.21. U is for ubiquitous

Data fusion methodologies could facilitate more continuous monitoring with the use of ubiquitous sensing technologies, addressing short-term limitations of WT: periodically downloading data from WT to free memory. Ideally, (ethically valid) ubiquitous sensing would (e.g.) relay technical information between technologies to harmonise data streams or; facilitate WT integration as the user enters different surroundings. With up to 10-trillion sensors connected to the internet in the next decade [52], systems/frameworks to identify, track and localise WT within all environments becomes difficult. Therefore, the utilisation of additional Positioning, Navigation and Timing (PNT) infrastructures to complement current systems (e.g. GPS) as well as the advent of the next generation of mobile connectivity[16] becomes paramount to achieve seamless and pragmatic ubiquitous WT.

2.22. V is for validation and verification

Increased WT awareness within healthcare usher's innovative methods to deliver modern approaches to improve patient treatment and management. Consequently, this sector is rife with opportunities where WT can offer efficient methodologies to gather sensitive data for more informed diagnosis. This may hasten development but conversely exposes users to poor WT, void of robust design with insufficient patient or clinician engagement; pragmatic utility; validation or verification. The creation of WT (inc. apps) and deployment within clinical settings is a contentious topic as it is difficult to determine if devices/products are (in vitro diagnostic) medical devices falling within the EU Medical Device Directive (MDD) framework [53]. (Devices or algorithms used in approved regulatory devices, e.g. CE[17] marking, are subject to suitable validation and verification procedures, often through clinical trials, to ensure that they perform as specified on the intended population.) Yet WT remains novel within healthcare where regulations require the manufacturer to perform internal verification processes only (ensuring basic compliance), often forgoing expensive and time consuming validation. No regulations exist for the robust capture and quantification of WT outcomes including expert guidance on suitable validation or verification procedures for any physiological outcome. Healthcare professionals should be cautious if adopting WT where a lack of transparency may conceal hidden barriers to robust patient assessment. For example, algorithms may utilise subjective thresholds to quantify outcomes that go unreported by the manufacturer [54].

2.23. W is for wearability

WT remains finely poised as a useful and pragmatic aid to inform healthy living. Yet, WT rides on waves of success from the latest mainstream gadget by a large corporation to show utility as a viable means to monitor the user during free-living, providing round the clock habitual data. Therefore, success is built on the fickle nature of consumerism and brand loyalty rather than an ability to quantify sensitive (clinically relevant) ageing or disease specific outcomes. Primarily, adoption of technology remains bound to the glamorous nature of good marketing or integration to smartphones. Many who receive or purchase WT engage with it for short periods, grow uninterested and take it off, reverting to usual clothing accessories. Others may not wear WT at all, or feel that it makes them stand out for the wrong reasons, as some ankle-based WT look like law-enforced tagging devices. Use of WT and body placement has a great deal to do with social acceptability [55] and may only become mainstream as perceptions change or devices become smaller and directly integrated into clothing or injected beneath our skin.

2.24. X is for X marks the spot

As previously discussed, depending on WT site(s) of attachment during movement related tasks and outcomes required (e.g. gait and step time) different algorithms may be used. Previous work detailed the effect of site variation (chest, lower back, right waist) on spatio-temporal gait outcomes during clinical testing [56]. Accordingly, correct WT placement is given careful consideration to ensure robust data collection and accurate measurement of movement related tasks, i.e.

[9] International Standards and Conformity Assessment for all electrical, electronic and related technologies.
[10] Institute for Electrical and Electronic Engineers.
[11] International Standards Organisation.
[12] PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses.
[13] SNOMED CT: www.snomed.org/snomed-ct.
[14] openEHR: www.openehr.org.
[15] Health Level Seven/Fast Healthcare Interoperability Resources (hl7.org/fhir).
[16] https://5g.co.uk.
[17] Ensures conformity to EU safety, health and environmental requirements. Other regulations apply depending on geographical area, e.g. The US Food and Drug Administration (FDA).

whether the site of attachment is best suited to capture the complete range of movement.

2.25. Y is for yourself

The power of WT lies in the ability to gather personalised data, allowing *you* to learn how poor lifestyle choices can influence negative trends in health (e.g. blood pressure). Typically, this is often referred to as self-monitoring, quantified-self or lifelogging. Robust data from valid and reliable WT can be used to aid medical diagnosis or treat the individual rather than relying solely on information about the collective. Data gathered by WT is unique to the wearer. Nevertheless, we are still in an age of discovery as abilities to detect and understand continuously evolve to inform ways to predict and prevent [57]. Ideally, strategies to target preventive medicine are developed from WT data gathered in the wild, where the complexities of normal daily living blur the ability of current algorithms to perform robustly. Additionally, WT data can contribute to self-care and effectively managing chronic disease exacerbations [58] by empowering a patient through WT data displays [59,60].

2.26. Z is for (generation) Z

Early exposure to technology breeds a familiarity that hastens abilities to adopt. Those exposed to technology (e.g. gaming consoles) in the home or computer literacy courses in school during adolescence may be considered early adopters and more willing to continuously use WT. In contrast, older generations may find it difficult to rationalise WT usage, simply because they never needed to: WT is a tool but to generation Z it can be a normal part of life [61]. The former must generally stay engaged through continuous instruction or novel experiences [62], whereas the latter are bombarded daily by technology. How current WT shortcomings with older generations map to generation Z in older age remain unknown or perhaps unwarranted. As the digital divide shrinks and disciplines like gerontechnology mature [63], WT will be become the norm with little or no learning curves required.

3. Summary and conclusion

The disruptive nature of WT is leading a slow evolution within modern healthcare. The power of WT as a pragmatic and clinically useful technology to aid patient diagnosis, treatment and care is becoming evident. This is due to its low-cost ability to gather habitual data in a discrete manner for longitudinal periods in any environment. Integration to the cloud provides readily available big data, facilitating the application of machine learning algorithms for novel outcomes. However, stringent data governance and appropriate validation and verification standards/procedures are significantly lacking within the field, with the former going through significant learning processes. Nevertheless, WT innovation is rife and still within a R&D phase of its technology life cycle. The simultaneous implementation of appropriate data regulation, validation/verification frameworks, ubiquitous integration to global networks and maturing of generations will see WT realise its potential.

Contributors

A Godfrey created the concept and framework for the paper, gathered references, and contributed to each draft and formatting of the paper to fit journal requirements.

V Hetherington created the concept and framework for the paper, gathered references, and contributed to each draft and formatting of the paper to fit journal requirements.

H Shum contributed to each draft and formatting of the paper to fit journal requirements.

P Bonato contributed to each draft and formatting of the paper to fit journal requirements.

NH Lovell gathered references, and contributed to each draft and formatting of the paper to fit journal requirements.

S Stuart created the concept and framework for the paper, gathered references, and contributed to each draft and formatting of the paper to fit journal requirements.

Conflict of interest

The authors declare that they have no conflict of interest.

Funding

This project was supported in part by the Engineering and Physical Sciences Research Council (EPSRC, reference:EP/M002632/1) and the Royal Society (reference: IE160609).

Provenance and peer review

Peer review was directed by Margaret Rees independently of Alan Godfrey (one of the authors and Guest Editor of the *Maturitas* special issue Modern Medicine for Healthy Ageing), who was blinded to the process.

References

[1] O. Amft, P. Lukowicz, From backpacks to smartphones: past, present, and future of wearable computers, IEEE Pervasive Comput. 8 (3) (2009) 8–13.
[2] T. Page, A forecast of the adoption of wearable technology, Int. J. Technol. Diffus. 6 (2) (2015) 12–29.
[3] D. Quesada-Gonzalez, A. Merkoci, Mobile phone-based biosensing: an emerging diagnostic and communication technology, Biosens. Bioelectron. 92 (2017) 549–562.
[4] SPFDE, et al., A digital compass for decision makers: toolkit on disruptive technologies, impact and areas for action, in: L. Probst (Ed.), Recommendations of the Strategic Policy Forum on Digital Entrepreneurship, European Commission, 2016, http://ec.europa.eu/DocsRoom/documents/17924.
[5] A. Godfrey, et al., Instrumented assessment of test battery for physical capability using an accelerometer: a feasibility study, Physiol. Meas. 36 (5) (2015) N71.
[6] O.V. Komogortsev, A. Karpov, Automated classification and scoring of smooth pursuit eye movements in the presence of fixations and saccades, Behav. Res. Methods 45 (1) (2013) 203–215.
[7] C. Wang, et al., A low-power fall detector balancing sensitivity and false alarm rate, IEEE J. Biomed. Health Inform. PP (99) (2017) 1–1.
[8] M. Cepeda, et al., Seasonality of physical activity, sedentary behavior, and sleep in a middle-aged and elderly population: the Rotterdam study, Maturitas 110 (2018) 41–50.
[9] S. Sakr, A. Elgammal, Towards a comprehensive data analytics framework for smart healthcare services, Big Data Res. 4 (2016) 44–58.
[10] IBM, 4 Vs of Big Data, (2017) 15 Feb 2018 http://www.ibmbigdatahub.com/infographic/four-vs-big-data.
[11] Cisco, Cisco Global Cloud Index: Forecast and Methodology, 2016–2021. White Paper, Cisco, San Jose, 2016.
[12] K. Bilal, et al., Potentials, trends, and prospects in edge technologies: fog, cloudlet, mobile edge, and micro data centers, Comput. Netw. 130 (2018) 94–120.
[13] B. Van Grootven, T. van Achterberg, The European Union's Ambient and Assisted Living Joint Programme: an evaluation of its impact on population health and well-being, Health Inform. J. (2016) p. 1460458216683535.
[14] M. Cozza, A. De Angeli, L. Tonolli, Ubiquitous technologies for older people, Pers. Ubiquitous Comput. 21 (3) (2017) 607–619.
[15] P. Bush, The craft of wearable wellbeing, Proceedings of the Third European Conference on Design4Health, Sheffield, 2015 13–16 July 2015, ISBN 978-1-84387-385-3 http://research.shu.ac.uk/design4health/wp-content/uploads/2015/07/D4H_Bush.pdf.
[16] T. Møller, S. Kettley, Wearable health technology design: a humanist accessory approach, Int. J. Des. 11 (3) (2017) 35–49.
[17] S. McDonald, et al., The state of the art and future opportunities for using longitudinal n-of-1 methods in health behaviour research: a systematic literature overview, Health Psychol. Rev. 11 (4) (2017) 307–323.
[18] S. McDonald, et al., Changes in physical activity during the retirement transition: a series of novel n-of-1 natural experiments, Int. J. Behav. Nutr. Phys. Act. 14 (1) (2017) 167.
[19] D.G. Armstrong, B. Najafi, M. Shahinpoor, Potential applications of smart multifunctional wearable materials to gerontology, Gerontology 63 (3) (2017) 287–298.
[20] R.C. King, et al., Application of data fusion techniques and technologies for wearable health monitoring, Med. Eng. Phys. 42 (2017) 1–12.
[21] B. Khaleghi, et al., Multisensor data fusion: a review of the state-of-the-art, Inf. Fusion 14 (1) (2013) 28–44.

[22] D. Barnard-Wills, The technology foresight activities of European Union data protection authorities, Technol. Forecast. Soc. Change 116 (2017) 142–150.
[23] C. Wang, et al., Friend or foe? Your wearable devices reveal your personal pin, Proceedings of the 11th ACM on Asia Conference on Computer and Communications Security, ACM, 2016, http://dx.doi.org/10.1145/2897845.2897847.
[24] A. Millecamps, et al., Understanding the effects of pre-processing on extracted signal features from gait accelerometry signals, Comput. Biol. Med. 62 (2015) 164–174.
[25] S. Del Din, et al., Free-living monitoring of Parkinson's disease: lessons from the field, Mov. Disord. 31 (9) (2016) 1293–1313.
[26] M. Mancini, et al., ISway: a sensitive, valid and reliable measure of postural control, J. Neuroeng. Rehabil. 9 (2012) 59–59.
[27] A. Godfrey, et al., iCap: instrumented assessment of physical capability, Maturitas 82 (1) (2015) 116–122.
[28] R. Mc Ardle, et al., What can quantitative gait analysis tell us about dementia and its subtypes? A structured review, J. Alzheimer's Dis. 60 (4) (2017) 1295–1312.
[29] L. Rocchi, et al., Balance testing with inertial sensors in patients with Parkinson's disease: assessment of motor subtypes, IEEE Trans. Neural Syst. Rehabil. Eng. 22 (5) (2014) 1064–1071.
[30] M. Dehghani, R.M. Dangelico, Smart wearable technologies: current status and market orientation through a patent analysis, 2017 IEEE International Conference on Industrial Technology (ICIT) (2017), http://dx.doi.org/10.1109/ICIT.2017.7915602.
[31] O2, The O2 Future of Mobile Life Report, (2017).
[32] PwC, The wearable future, Consumer Intelligence Series, PricewaterhouseCoopers (PwC), 2014.
[33] S. Webb, How Will Wearables Disrupt the Healthcare Landscape? Accenture, 2015.
[34] Accenture, Healthcare for here or to go? in: D. Boston, M. Kovach (Eds.), Insight Driven Health: Healthcare for Here or to Go? Accenture Consulting, 2015.
[35] K.J. Kubota, J.A. Chen, M.A. Little, Machine learning for large-scale wearable sensor data in Parkinson's disease: concepts, promises, pitfalls, and futures, Mov. Disord. 31 (9) (2016) 1314–1326.
[36] A. Godfrey, et al., A continuous wavelet transform and classification method for delirium motoric subtyping, IEEE Trans. Neural Syst. Rehabil. Eng. 17 (3) (2009) 298–307.
[37] P. Xiong, et al., Design of an accurate end-of-arm force display system based on wearable arm gesture sensors and EMG sensors, Inf. Fusion 39 (2018) 178–185.
[38] N.Y. Hammerla, et al., PD disease state assessment in naturalistic environments using deep learning, AAAI (2015), https://www.aaai.org/ocs/index.php/AAAI/AAAI15/paper/view/9930.
[39] D. Ravì, et al., Deep learning for health informatics, IEEE J. Biomed. Health. Inf. 21 (1) (2017) 4–21.
[40] Appendix B – the WEKA workbench A2 – Witten, Ian H, in: E. Frank, M.A. Hall, C.J. Pal (Eds.), Data Mining, fourth edition, Morgan Kaufmann, 2017, pp. 553–571.
[41] M. Buus-Frank, Nurse versus machine: slaves or masters of technology? J. Obstet. Gynecol. Neonatal Nurs. 28 (4) (1999) 433–441.
[42] C. Ladha, et al., Toward a low-cost gait analysis system for clinical and free-living assessment, 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (2016), http://dx.doi.org/10.1109/EMBC.2016.7591086.
[43] C. Ladha, et al., Dog's life: wearable activity recognition for dogs, Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing, ACM, 2013.
[44] M.M. Jackson, et al., FIDO-facilitating interactions for dogs with occupations: wearable dog-activated interfaces, Proceedings of the 2013 International Symposium on Wearable Computers, ACM, 2013.
[45] E. Saner, Barks and Bytes: the Rise of Wearable Tech for Pets, (2017) 22 Feb 2018; Available from: www.theguardian.com/lifeandstyle/2017/feb/03/wearable-tech-for-pets.
[46] J. Serpell, et al., Current challenges to research on animal-assisted interventions, Appl. Dev. Sci. 21 (3) (2017) 223–233.
[47] P.M. Dall, et al., The influence of dog ownership on objective measures of free-living physical activity and sedentary behaviour in community-dwelling older adults: a longitudinal case-controlled study, BMC Public Health 17 (1) (2017) 496.
[48] N.D. Schüll, Data for life: wearable technology and the design of self-care, BioSocieties 11 (3) (2016) 317–333.
[49] R. Duus, M. Cooray, How We Discovered the Dark Side of Wearable Fitness Trackers, (2015) 19 Jun 2015 22 Feb 2018; Available from: https://theconversation.com/how-we-discovered-the-dark-side-of-wearable-fitness-trackers-43363.
[50] S. Del Din, A. Godfrey, L. Rochester, Validation of an accelerometer to quantify a comprehensive battery of gait characteristics in healthy older adults and Parkinson's disease: toward clinical and at home use, IEEE J. Biomed. Health Inf. 20 (3) (2016) 838–847.
[51] IEEE, IEEE Standard for Wearable Cuffless Blood Pressure Measuring Devices, (2014), pp. 1–38 IEEE Std 1708–2014.
[52] M. Lisi, A digital new world the big fusion between ubiquitous localization (GNSS), sensing (IOT) and communications (5G), GEOmedia 20 (6) (2017).
[53] F. Lucivero, B. Prainsack, The lifestylisation of healthcare? 'Consumer genomics' and mobile health as technologies for healthy lifestyle, Appl. Transl. Genom. 4 (2015) 44–49.
[54] G. Barry, et al., Defining ambulatory bouts in free-living activity: impact of brief stationary periods on bout metrics, Gait Posture 42 (4) (2016) 594–597.
[55] C. Zeagler, Where to wear it: functional, technical, and social considerations in on-body location for wearable technology 20 years of designing for wearability, Proceedings of the 2017 ACM International Symposium on Wearable Computers, ACM, 2017.
[56] S. Del Din, et al., Measuring gait with an accelerometer-based wearable: influence of device location, testing protocol and age, Physiol. Meas. 37 (10) (2016) 1785–1797.
[57] N. Alshurafa, J. Hester, Personalized medicine in the wearable era: translational barriers and call to action, Proceedings of the First International Workshop on Human-centered Sensing, Networking, and Systems, ACM: Delft, Netherlands, 2017, pp. 37–42.
[58] A. Darkins, et al., Care coordination/home telehealth: the systematic implementation of health informatics, home telehealth, and disease management to support the care of veteran patients with chronic conditions, Telemed. e-Health 14 (10) (2008) 1118–1126.
[59] M. Swan, The quantified self: fundamental disruption in big data science and biological discovery, Big Data 1 (2) (2013) 85–99.
[60] B. Shneiderman, C. Plaisant, B.W. Hesse, Improving healthcare with interactive visualization, Computer 46 (5) (2013) 58–66.
[61] K. Wondergem, Here Comes Z. Strategies To Engage A New Generation Of College Students, (2017) 9 Sept 2017 22 Feb 2018; Available from: https://elearningindustry.com/engage-a-new-generation-of-college-students-strategies.
[62] E. Guglielman, The Ageing Brain: Neuroplasticity and Lifelong Learning vol. 29, (2012), pp. 1–7 eLearning Papers.
[63] J.A. Delello, R.R. McWhorter, Reducing the digital divide: connecting older adults to iPad technology, J. Appl. Gerontol. 36 (1) (2017) 3–28.