A vision for the future of wearable sensors in spine care and its challenges: narrative review

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Objective: This review aimed to: (I) provide a brief overview of some topical areas of current literature regarding applications of wearable sensors in the management of low back pain (LBP); (II) present a vision for a future comprehensive system that integrates wearable sensors to measure multiple parameters in the real world that contributes data to guide treatment selection (aided by artificial intelligence), uses wearables to aid treatment support, adherence and outcome monitoring, and interrogates the response of the individual patient to the prescribed treatment to guide future decision support for other individuals who present with LBP; and (III) consider the challenges that will need to be overcome to make such a system a reality.

Background: Advances in wearable sensor technologies are opening new opportunities for the assessment and management of spinal conditions. Although evidence of improvements in outcomes for individuals with LBP from the use of sensors is limited, there is enormous future potential.

Methods: Narrative review and literature synthesis.

Conclusions: Substantial research is underway by groups internationally to develop and test elements of this system, to design innovative new sensors that enable recording of new data in new ways, and to fuse data from multiple sources to provide rich information about an individual's experience of LBP. Together this system, incorporating data from wearable sensors has potential to personalise care in ways that were hitherto thought impossible. The potential is high but will require concerted effort to develop and ultimately will need to be feasible and more effective than existing management.

Keywords: Wearable sensors; low back pain (LBP); model of care; posture; biopsychosocial

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Introduction

Wearable sensors have become pervasive in society. Most individuals carry or wear some type of device that measures some aspect of their life. This ranges from simple measures of movement (1) and location (2) made by smart phones, to comprehensive analysis of health measures derived from specialised devices that, in addition to movement, measure biological variables such as heart rate and estimate parameters such as sleep, stress, and activity level (3). Wearable devices and their derived measures are being increasingly implemented to aid management of a diverse array of health conditions including low back pain (LBP) (4). This has most commonly related to evaluation of physical activity (4), but with advances in technology and analysis, more sophisticated assessments are beginning to be possible, such as measurement of posture and movement in the real world (5,6), which has been the topic of several extensive systematic reviews (4,6,7). Wearable sensor technology is rapidly evolving and the potential utility for LBP management is immense.

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This paper aims to: (I) provide a brief overview of some topical areas of current literature regarding applications of wearable sensors in management of LBP; (II) present a vision for a future comprehensive system that integrates wearable sensors to measure multiple parameters in the real world that contributes data to guide treatment selection (aided by artificial intelligence), uses wearables to aid treatment support, adherence and outcome monitoring, and interrogates the response of the individual patient to the prescribed treatment to guide future decision support for other individuals who present with LBP; and (III) consider the challenges that will need to be overcome to make such a system a reality. We present the following article in accordance with the Narrative Review reporting checklist (available at https://jss.amegroups.com/article/view/10.21037/jss-21-112/rc).

Methods

This narrative review presents a synthesis of available literature regarding a broad range of issues. The intention was not to systematically review the literature for each topic, but to present current opinions, recent findings and identify new directions for application of wearable sensors in spine care.

Overview of current application of wearable sensors in management of LBP

The most common application of wearable sensors in the management of LBP is for activity monitoring (4). In most cases this has been straightforward assessment of activity level of patients for assessment (8) or to monitor outcome after treatments, including surgery (4,9). Wearable sensors have also been used to assess not just whether a person moves, but how they move, such as evaluation of the spinal curvature/posture and movement (5,6) and movement patterns (7,10) during function and sometimes in the real-world, outside the treatment clinic. Several trials have used wearables to provide feedback for training, with variable success (11-14). This has also been integrated into gamified approaches to movement training (15,16). Most research has provided evidence for the validity and potential utility of the devices (17-19), but evidence on whether patient outcomes are improved by such application is scarce (20-22). Trials of interventions that have used wearable sensors to address a single feature in LBP [e.g., improve posture (23)] have had limited success in reducing pain, which is not surprising considering the heterogeneity and complexity of the condition.

More complex applications of wearables to treatment for LBP have been trialled. These include use of activity sensors to monitor and guide progress of a treatment aimed to improve self-management of LBP (24). Data from wearable sensors was used to monitor progress and guide dosage of physical activity, education and exercises for strength and flexibility. Despite the sophistication of the model of application of intervention, the results from this randomised controlled trial, indicated only a slight and probably not clinically important improvement in outcome relative to intervention unsupported by data from wearable sensors (25). This finding concurs with the observation that although self-management approaches that include exercise are more effective than no treatment, there is little difference in outcome between different models of application of this management strategy (26). From one perspective this might suggest that the hype of wearable sensors is unfounded, but from another it might suggest that we are not yet capturing the full potential of wearables.

Measures other than movement are also being developed and evaluated. Recordings of electromyography (EMG) from back muscles with wearable sensors have been available for many years (27) and have been implemented clinical interventions (28). Advances in technology, such as wearable "tattoo" electrodes provide promise (29). Analysis algorithms to automate analysis of data are being developed and tested (30). Whether data derived from wearable EMG can guide effective treatment has not yet been confirmed.

Estimation of sleep parameters using activity monitoring devices is also beginning to provide information regarding the association between sleep and LBP (31,32). Home-based electroencephalography (EEG) measures with wearable devices are also becoming available and applied to provide more detailed evaluation of sleep architecture (33), but not yet in LBP. Also not yet applied to LBP is the use of wearable sensors to evaluate physiological parameters associated with stress such as heart rate variability and pulse transit time from electrocardiography (ECG) and photoplethysmography recordings (34-36) and novel sensors for detection of cortisol in sweat (37,38).

In summary, there has been widespread use of wearables to monitor physical activity in LBP. This provides greater accuracy of monitoring of treatment outcomes and when integrated into a treatment support system, small benefits for treatment outcomes have been achieved. The question that remains is whether there is further potential to generate larger benefits for individuals with spinal complaints using a

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system that integrates data from multiple wearable sensors to provide a more comprehensive picture of an individual's presentation that could provide refined information for treatment selection and provision?

A vision for a future comprehensive system using wearable sensors

Advances in technology are beginning to present possibilities to go beyond the use of sensors to simply *enhance* the application current management practices, and instead lead to a reconceptualization of the entire system for management of LBP. The following provides an overview of some key issues that plague the current management system and what to consider for a vision for an alternative system that might be possible with these technological advances.

Current LBP management

Current management of LBP generally depends on a limited number of assessments that capture narrow view of specific aspects of the state of the individual at a single timepoint (39) or over a limited period of time (40), or require recall of events/exposures (41). These assessments are generally made in an artificial setting (i.e., in a clinical facility when the individual is aware they are being scrutinised) (42,43). This is unlikely to replicate the context within which an individual lives (7) or the performance of the individual in their usual functional environment (40). The scope of assessments is generally influenced by the discipline of the clinician undertaking the assessment (44). This information is then used to select from a limited array of treatments (or referral to another clinician) that are most commonly applied in a generic one-size-fits-all manner, perhaps with some individualisation of dosage (45). Treatments may include application of an intervention, prescription of a drug, a home program or a supported self-management program (45). The outcome is reviewed to evaluate success or failure, followed by subsequent progression of treatment, change to a different treatment approach (often using a trial-and-error stepped approach) (46), or perhaps referral to another clinician. There are many challenges: assessments are limited in scope and detail and may not reflect actual lived experience (7,42); treatments are narrowly applied (46); treatment effects are challenged by poor adherence (47); and the individual's response to treatment is not used to inform future decision making for others.

It could be argued that this model of care is unable to address the complexity of LBP and other spinal complaints. It is accepted that LBP is characterised by a huge array of biopsychosocial features that interplay uniquely for each individual who has the condition (48). Adding complexity is the recognition that LBP is a fluctuating condition that varies over time (49,50), and with a unique set of features driving this variation (51,52). These realities imply personalized care is likely to be needed. From one perspective it could be argued that this complexity is too great, and we should search for simple solutions that make some impact, even if small. The alternative perspective is to find ways to develop complex interventions (53) and support the decisions regarding care (54). This will not be straightforward; modelling work suggests that integration of multiple features for personalisation of care quickly becomes impossible once more than a handful of factors are considered (55). Wearable sensors might be part of the solution.

New potential from advances in technology

Advances in technology have enhanced the potential to evaluate features with potential relevance to LBP in the real world and to make these measures over an extended period time (56). These advances are beginning to make it possible to conceptualise the possibility to pervasively collect a broad array of variables across biological, psychological, and social domains in the real world as a person lives their life. These data could be interrogated to identify if and how each (or the interaction between them) relates to an individual's LBP experience, including any relationship to fluctuation of the condition. Recent work has highlighted that LBP is mostly experienced as an ongoing condition characterised by fluctuations in symptoms (sometimes referred to as flares) (49,57). Qualitative research suggests people often consider themselves to have LBP, even when they are in remission (58). Wearable sensors would lie at the core of analysis of the factors that could explain the fluctuation of the condition, and that are potentially modifiable by treatments.

In the biological domain, research is already providing some insight into the potential utility of data collected in the real world, albeit from a limited set of domains/measures (5,51). For instance, although LBP can interfere with sleep, real-world data from wearable sensors and information that a user inputs into a smartphone application show that for some individuals a night of poor sleep quality (but not

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quantity) increases risk for a flare of the condition (51). New simplified EEG sensor systems that involve a headband are being applied to evaluate sleep architecture and provide potential for more detailed analysis of this relationship (59). For some individuals, transient exposure to a day of low physical activity is also a risk factor for flare while exposure to moderate activity is protective for flare (51). Potential to evaluate biological features in the real-world might also reveal a relevance of factors for LBP that have not yet been considered (because of inability to make appropriate measures), factors that might be relevant for some individuals but not others, or factors that have been largely dismissed or criticised based on data assessed in artificial settings.

There has been substantial debate regarding the relevance of posture and movement for LBP (60). Several reviews have concluded that there is an absence of supporting evidence (61,62). Although differences in kinematics and posture between individuals with and without pain are common in the literature [e.g., (63,64)], this does not confirm that it is relevant for their condition. Most studies measure spine motion and posture in cross-sectional studies in a laboratory (65) with unclear relevance to the real-world, use measures that have not been validated (66), or rely on subjective reporting of exposure to posture/movements (67). Many studies measure variables such as range of motion which have unclear relevance for interpretation of real-world function which involves consideration of multiple factors such as coordination between segments (68). Most studies use small sample sizes, cannot exclude bias, and measure an enormous variety of parameters that are not consistently applied between studies (60). Further, most studies assume that support for the relevance of a feature of posture or movement to LBP depends on evidence for its presence in individuals with LBP, but not those without LBP (61), and that all individuals with LBP would present in a similar manner (69). These assumptions ignore the reality of individual variation and that the relevance of a posture or movement for an individual's LBP is likely to depend on the exposure, and other contextual or individual factors. Although individuals without LBP might present with a specific feature (such as flexion of the spine during lifting), that does not preclude the possibility that that this feature of movement is problematic and provocative of symptoms for an individual with LBP. It is well known that individuals with LBP that adopt different movement patterns, and in some cases a cluster of movement and posture features are identified that can be used to allocate individuals to subgroups (64,70,71). It is plausible that continuous assessment of movement and posture in the real-world enabled by advances in wearable technology might reveal an association between specific postures and movements and fluctuations of the condition for an individual and provide meaningful guidance for treatment selection. Algorithms are being developed to classify postures, movements, and transitions in real world settings (72,73).

Although measures in the psychological domain are more challenging to collect in an automated way, advances in technologies and analysis are providing potential to estimate some psychological factors from biological correlates. For instance, algorithms have been developed to estimate stress from measures that include heart rate variability (35). Sensors have been developed, but not yet widely available, to measure cortisol and other molecules from sweat that might provide additional information of stress (74) and immune signalling (75), that both have potential relevance for LBP. Of course, not all psychological features of potential relevance to LBP can be automatically obtained. For measures of many psychological phenomena (e.g., fear of pain/movement; pain catastrophising; mood; depression; self-efficacy) there may be no simple physiological analogue, and user input is likely to be required. Life-logging applications (35,51) present possibility to prompt users to input potentially relevant data at specific times to integrate with wearable sensor data. The individual's experience of pain itself is not a simple measure and depends on user input.

Although transient exposure to social factors is also likely to require user input into life-logging applications, GPS data from wearable sensors is already being interrogated for information regarding social engagement and broader aspects of function (76). Data from smartphones and wearables related to communication and voice characteristics is also being used to quantify social exchanges (with mechanisms to protect privacy) in mental health conditions (77-79).

Together, there is potential to capture complex data across multiple domains to provide unrivalled data of an individual's experience. Integration of such data is likely to provide a foundation to shift the paradigm of LBP management towards truly personalised selection of intervention. As a critical steppingstone, the availability of new technologies to provide new insights an individual's condition, demands a new phase of discovery research to identify relevant factors prior to integration into health care.

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A future comprehensive system for management of LBP enabled by wearable sensors

With the potential for collection of detailed ongoing real-world data regarding an array of potentially relevant factors across biological, psychological and social domains using wearable sensors and user input, a new model of management of LBP is possible. A vision for such a system could include: (I) assessment and decision support; (II) treatment support; and (III) ongoing refinement of more precise personalisation of care. An overview of the model is presented in *Figure 1*.

Assessment and decision support

On presentation to a health care provider, the future might include provision of a suite of sensors and a user input interface to the individual with LBP to enable evaluation of an array of features in the real world. *Table 1* presents a summary of many of the wearable sensor types that are currently available and their potential utility. These data could be automatically interrogated (using machine learning algorithms, or other data classification methods) to extract measures that relate to an array of variables across domains (e.g., sleep quality; time in specific postures; activity level; variation in stress; social interaction; interaction between the multiple domains; etc.). These data could be integrated with other relevant information of the individual and their condition [e.g., imaging (80,81), history (82), omics (genomic; transcriptomic; proteomic; metabolomic data) (83,84), likely neurobiological mechanisms contributing to pain (85,86)]. The large individual dataset would then be interrogated to identify the factors (and interactions between factors) that are relevant for the individual's experience of LBP (such as those that fluctuate with the waxing and waning of LBP). These would serve as potential targets for treatments to be selected from an available suite of management options.

Based on the sheer number of variables to consider, mechanisms for decision support would be necessary. Advances in application of artificial intelligence make this possible. Neither the use of computerised decision support (87), nor the application of artificial intelligence (88) is new in LBP. What is new is the diversity of available data upon which decisions can be made. For this system to be possible the relationship between each factor and its responsiveness to treatments would also need to be known, how they might interact, and whether this responsiveness is affected by other elements of the individual patient's unique profile. Ideally, prediction of potential effects of matched treatments would be informed by a database built from data accrued from all previous individuals with LBP whose data has been interrogated in this manner (see below). Thus, comprehensive assessment, including that provided by wearables, could provide a foundation for personalisation of care beyond what is even possible to imagine today.

Treatment support

Application of treatment could be supported by data derived from wearable sensors. Wearable sensor data can provide biofeedback (89), alert to problems (12), and monitoring of progress (25). Already data has been interrogated to track improvement of function such as physical activity and gait, and this information has been used to guide refinement of care (25). Data of spine posture and movement has been used to monitor and provide feedback as a component of motor learning interventions to train changes in performance (5). This reinforces the potential for wearable sensors to provide data to support care but, as yet, without comprehensive consideration of other variables.

There has been considerable work undertaken to develop electronic/mobile health (eHealth/mHealth) care resources for LBP that address different elements relevant to the pain experience (90-92) and some of these already incorporate data from wearable sensors (5,93), including social factors (94). Additional work is required to enhance the breadth of features that can be targeted by mHealth interventions, and to incorporate the use of innovative new sensors.

There are considerable advantages to support treatment with data from wearable sensors. First, remote application of treatment through telehealth applications (which currently rely on video assessment) (95) would be facilitated by provision of objective real time data from wearable sensors. Second, a major barrier to treatment efficacy is adherence to care (96); wearable sensors might contribute to strategies to address this issue (e.g., enhanced motivation to promote adherence (97); identification of non-adherence (98). Third, ideally data from the wearable sensors (and life-logging) that is recorded during the management period would be automatically uploaded to a server/cloud, automatically interrogated, used to modify (progress or change) treatments, and fed to clinical providers for review/alert.

Ongoing refinement of more precise personalisation of care

A major potential benefit from a system that provides detailed and automatically analysed data, along with

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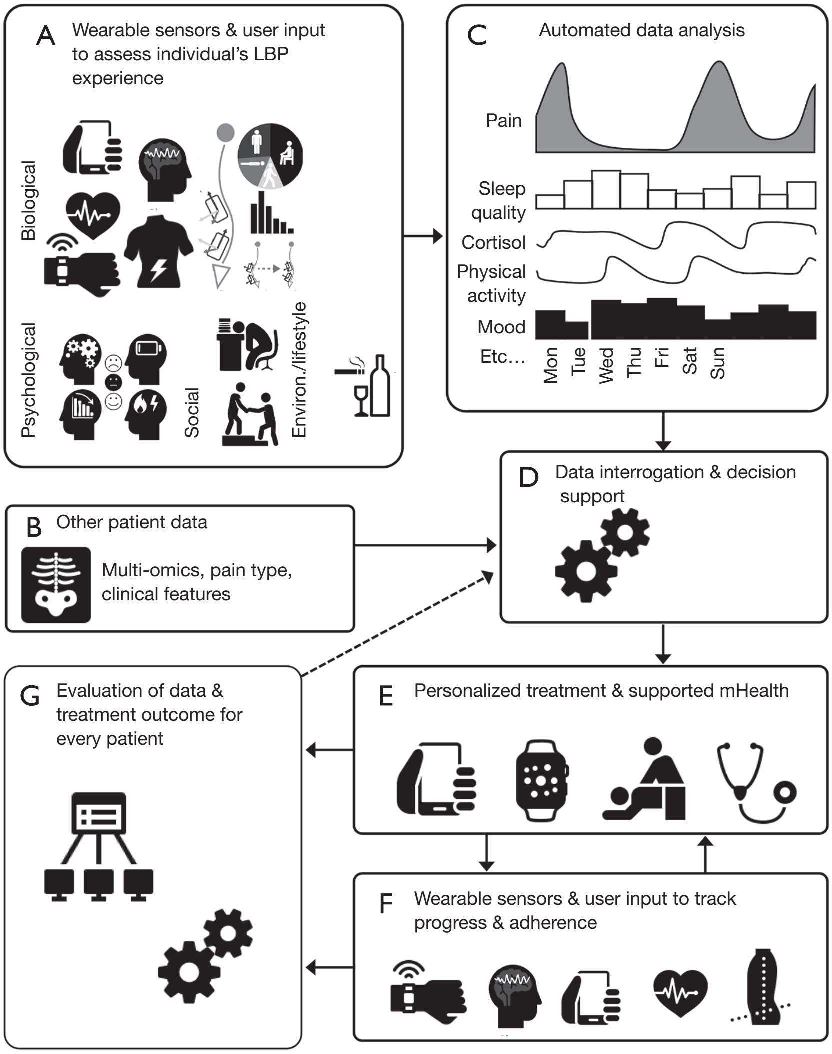

Figure 1 Framework for integration of wearable sensor data to guide personalized management of low back pain. (A) Continuous data from multiple domains are recorded using wearable sensors in the real world. User input data are recorded using apps to record factors that cannot be recorded with wearables (e.g., pain, psychological variables, etc.); (B) other patient data are collected to contribute to decision support. This might include multi-omics data (genomic, transcriptomic, proteomic, metabolomic, etc.), clinical features, imaging, clinically identified primary pain mechanism grouping, etc.; (C) data from wearable sensors are analysed using automated algorithm-based analysis supported by machine learning and combined with user input data; (D) all data inputs are interrogated to evaluation the complex interaction between multiple dimensions and low back pain experience using analytic methods including artificial intelligence to provide decision support for allocation of tailored interventions; (E) personalized management plan is provided that, depending on the individual patient, could include "in person" treatment and a suite of mobile Health (mHealth) solutions for self-management. mHealth solutions might include use of wearable data to support treatment (e.g., biofeedback, motivation, etc.); (F) wearable sensors and user input apps are used to monitor treatment adherence and evaluation of progress. These data would be fed back to a treating clinician; (G) all data from individual patients, the applied treatments and the treatment outcomes are uploaded to a central server to continue to build the accuracy of decision support. LBP, low back pain.

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Table 1 Examples of wearable sensors with potential application to low back pain

Sensors	Measurements	Example clinical information
Activity		
Accelerometer	Activity level; step count; sedentary time; speed	Physical activity; energy expenditure; sleep
Pedometer	Steps count	Physical activity
Global positioning system (GPS)	Distance travelled; location	Function; social interaction; participation
Movement/posture/muscle activity		
Magnetic (magnetometer), angular rate (gyroscope) and gravity (accelerometer) sensors	Orientation relative to earth	Joint angle/posture or relative angle/posture when 2 sensors are incorporated
Strain sensors (e.g., fibre optic; inductance)	Length change	Spine—movement/posture; chest—breathing
Goniometer	Angle	Joint angular motion
Pressure sensor	Force	Shoe—foot contact; ground reaction forces; inverse dynamics; chest—breathing
Electromyography (single channel and grid)	Muscle activity	Contraction/relaxation of muscle
Physiological		
Photoplethysmography (PPG)	Heart rate; heart rate variability; heart rate recovery; oxygen saturation; sleep stages; cardiac output	Exercise tolerance; stress
Electrocardiography (ECG)	Heart rate; heart rate variability	Exercise tolerance; stress
Electroencephalography (EEG)	Brain activity	Sleep; sleep architecture; attention
Near Infrared spectroscopy	Muscle oxygenation; Oxy-, deoxy- and total haemoglobin; cerebral oxygenation	Oxygen saturation in muscle
Biochemical sensors (e.g., epidermal; sweat; transdermal)	Cortisol; pH; electrolytes; glucose; lactate	Stress; nutrition; fatigue
Skin conductance		
Temperature	Body temperature	Temperature; heat stress
Other measures		
Video (smart glasses)	Activity; social interaction	
Sound	Language analysis; ambient sound	Social interaction; environmental context; social ambience measures
Light	Ambient light	Environmental context

information of applied treatments and the response to these treatments, is that with each new participant, additional data are provided for refinement of decision support. Theoretically, the precision of decision support for the allocation of treatments would likely improve. Similar approaches have been applied in LBP to refine self-management using a limited number of variables (99).

Challenges to overcome to make the system a reality

Although elements of the proposed system are available and have been trialled in LBP, there is considerable work to be done to make it a reality. Major considerations include those that relate to sensors/sensor data, treatment selection,

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availability of mHealth options, treatment provision and governance/security/privacy and usability of wearable sensors.

In terms of wearable sensors there are physical and technical issues that need to be addressed. From a physical perspective, sensors should not restrict or influence function. An ideal sensor would be one that a participant agrees to wear but is unaware of, once in use. One that a participant has little to do to affix, remove, recharge or to transfer data. How to make this possible is not yet clear, but many attempts have been made to meet these requirements. For instance, simplified EEG system have been designed with electrodes embedded in a headband (59), various sensors have been embedded in clothing (100,101), fibre optic sensors have been used in flexible materials to measure movement (102), and sensors for electrical signals (e.g., EMG and ECG) are available as removable "tattoos" (29). From a technical perspective there are issues of battery life/charging (103) and transmission or recording of data. New electronic designs are being trialled for options such as stretchable materials with integrated energy storage (104). Innovative methods to harvest energy from body heat and kinetic energy from body movement are possible (105). Ideally, data would be automatically uploaded to a server for analysis and interrogation (106). Current technology generally requires transfer to a computer or smartphone as an intermediate step to transfer to permanent storage. Direct transfer is not yet possible. As new technologies and new data management opportunities become available that enable new features to be measured in new ways, it will be necessary to undertake discovery research to evaluate the potential relevance for LBP management. Other health economic evaluation will be critical to consider the balance between costs and benefits of different application methods. For instance, analysis of sleep from EEG data might be more cumbersome and less feasible than use of movement sensors, but this sacrifice of ease might be outweighed by the additional information that can be extracted from analysis of sleep architecture from EEG (59). Even if movement sensors were considered acceptable, there is also the consideration of validity of estimation of sleep parameters from different combinations and placements of accelerometers, some of which are more acceptable than others (107).

Data analysis poses multiple challenges. There are many challenges for analysis of data from sensors in the real world. For instance, position and movement are generally evaluated by fusion of data from accelerometers, gyroscopes and magnetometers, but these measures are impacted by linear accelerations, drift and metal objects, respectively and require application of algorithms to identify and remove the impact of these factors (108-110). Accuracy and validity of measures is paramount and is currently variable (7). There will be challenges with interpretation of data. For motion sensors, any sensor system that involves markers attached to the skin will be influenced by skin motion (111).

Availability of meaningful data is paramount. A major hurdle is the challenge of classification of daily-life behaviours (112-114). For instance, from movement data it is critical to identify different functions and tasks (e.g., sitting, standing, walking and lifting) to reduce the diversity of activities, postures, movements to an interpretable set of meaningful variables (e.g., variation of spine posture in sitting). This requires development of application of mathematical rules/methods that must be validated. In many cases, it is probable that classification and analysis will be facilitated by fusion of data from multiple sources. For instance, interpretation of stress from data of heart rate variability requires fusion with context data [e.g., to differentiate heart rate responses between those induced by physical activity and those induced by stressful events (35)].

Once the challenges of data collection and analysis are overcome the challenge shifts to using this information for selection. This depends on availability of treatments to address the identified parameters, methods to optimise the success of treatments that take advantage of the new technologies, and potential to predict the response to treatments (and the interaction between them). This step might require a reconsideration of the literature. For instance, when considering the suite of treatments, it is plausible that some treatments that have been found to be ineffective when applied in generic manner to the heterogeneous group with LBP might be effective to address specific relevant features for and individual patient. Further, a key element of interventions implemented using wearables is behaviour change. Although change is achievable, it is often discussed that interaction with wearable devices and platforms can be short lived (115,116). Adaptive interventions are required to maintain engagement (117) and pre-empt non-adherence (118).

For a proposed system to be viable, the health system needs to enable the inclusion of this model of care (115). Co-development with clinicians and patients will be necessary to ensure that the sensors and system have utility, and co-development with health services will be necessary to ensure the potential to integrate the model of care. There will be security and governance considerations regarding access to

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data (3) and cybersecurity tools such as blockchain might provide a solution (119). Models of payment will need to be considered and differ between health systems. It will be critical to consider issues of cost effectiveness, feasibility, and convenience (115). The proposed model of care might not be cost effective to use for all participants. Perhaps a "light" version is necessary for individuals at low risk of poor outcome, and the "full" intensive version is reserved for those at high risk of poor outcome. These decisions might be supported by tools such as StartBack (a LBP screening tool to stratify care) approach to risk stratification (120).

Some of these challenges will need to be considered sequentially, and some in parallel. First it is critical to resolve, with discovery research, whether new wearable sensor technologies provide data that have plausible mechanistic associations with an individual's condition. Second, there will need to be co-design with clinicians, patients, industry and health services to build the elements of the system to ensure it is feasible and that utility of a system is optimised. Third, the efficacy and cost effectiveness of the system will need to be tested. Fourth, the system will need to be future proofed to embrace new technologies, new knowledge and new methods become available. If effective, the system has great potential for application to other conditions.

Conclusions

This paper aimed to provide an overview of how wearable sensors might be integrated into a model of personalised and supported care for LBP (and other spinal conditions). Major advantages of this system are real world measurement (over time) of data from multiple domains, fusion of data from different sources, decision support (that improves over time as data from more patients are added), and treatment support. Recent technological advances are bringing this closer to reality. Although exciting, it cannot be assumed that this more complex perspective will be more effective than simpler forms of care, that will need to be tested, as will the cost effectiveness of the approach.

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References

1. Sinha VK, Patro KK, Pławiak P, et al. Smartphone-Based Human Sitting Behaviors Recognition Using Inertial Sensor. Sensors (Basel) 2021;21:6652.
2. Tosic L, Goldberger E, Maldaner N, et al. Normative data of a smartphone app-based 6-minute walking test, test-retest reliability, and content validity with patient-reported

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outcome measures. J Neurosurg Spine 2020. [Epub ahead of print].
3. Bayoumy K, Gaber M, Elshafeey A, et al. Smart wearable devices in cardiovascular care: where we are and how to move forward. Nat Rev Cardiol 2021;18:581-99.
4. Amin T, Mobbs RJ, Mostafa N, et al. Wearable devices for patient monitoring in the early postoperative period: a literature review. Mhealth 2021;7:50.
5. Kent P, Laird R, Haines T. The effect of changing movement and posture using motion-sensor biofeedback, versus guidelines-based care, on the clinical outcomes of people with sub-acute or chronic low back pain-a multicentre, cluster-randomised, placebo-controlled, pilot trial. BMC Musculoskelet Disord 2015;16:131.
6. Simpson L, Maharaj MM, Mobbs RJ. The role of wearables in spinal posture analysis: a systematic review. BMC Musculoskelet Disord 2019;20:55.
7. Papi E, Koh WS, McGregor AH. Wearable technology for spine movement assessment: A systematic review. J Biomech 2017;64:186-97.
8. Lotzke H, Jakobsson M, Gutke A, et al. Patients with severe low back pain exhibit a low level of physical activity before lumbar fusion surgery: a cross-sectional study. BMC Musculoskelet Disord 2018;19:365.
9. Inoue M, Orita S, Inage K, et al. Objective evaluation of postoperative changes in real-life activity levels in the postoperative course of lumbar spinal surgery using wearable trackers. BMC Musculoskelet Disord 2020;21:72.
10. Elgueta-Cancino E, Schabrun S, Danneels L, et al. Validation of a Clinical Test of Thoracolumbar Dissociation in Chronic Low Back Pain. J Orthop Sports Phys Ther 2015;45:703-12.
11. Brakenridge CL, Fjeldsoe BS, Young DC, et al. Evaluating the effectiveness of organisational-level strategies with or without an activity tracker to reduce office workers' sitting time: a cluster-randomised trial. Int J Behav Nutr Phys Act 2016;13:115.
12. Ribeiro DC, Sole G, Abbott JH, et al. The effectiveness of a lumbopelvic monitor and feedback device to change postural behavior: a feasibility randomized controlled trial. J Orthop Sports Phys Ther 2014;44:702-11.
13. Thanathornwong B, Suebnukarn S. The Improvement of Dental Posture Using Personalized Biofeedback. Stud Health Technol Inform 2015;216:756-60.
14. Matheve T, Brumagne S, Demoulin C, et al. Sensor-based postural feedback is more effective than conventional feedback to improve lumbopelvic movement control in patients with chronic low back pain: a randomised controlled trial. J Neuroeng Rehabil 2018;15:85.
15. Hügli AS, Ernst MJ, Kool J, et al. Adherence to home exercises in non-specific low back pain. A randomised controlled pilot trial. J Bodyw Mov Ther 2015;19:177-85.
16. Meinke A, Peters R, Knols R, et al. Exergaming Using Postural Feedback From Wearable Sensors and Exercise Therapy to Improve Postural Balance in People With Nonspecific Low Back Pain: Protocol for a Factorial Pilot Randomized Controlled Trial. JMIR Res Protoc 2021;10:e26982.
17. Khurelbaatar T, Kim K, Lee S, et al. Consistent accuracy in whole-body joint kinetics during gait using wearable inertial motion sensors and in-shoe pressure sensors. Gait Posture 2015;42:65-9.
18. Beange KHE, Chan ADC, Beaudette SM, et al. Concurrent validity of a wearable IMU for objective assessments of functional movement quality and control of the lumbar spine. J Biomech 2019;97:109356.
19. Mjøsund HL, Boyle E, Kjaer P, et al. Clinically acceptable agreement between the ViMove wireless motion sensor system and the Vicon motion capture system when measuring lumbar region inclination motion in the sagittal and coronal planes. BMC Musculoskelet Disord 2017;18:124.
20. Amorim AB, Pappas E, Simic M, et al. Integrating Mobile-health, health coaching, and physical activity to reduce the burden of chronic low back pain trial (IMPACT): a pilot randomised controlled trial. BMC Musculoskelet Disord 2019;20:71.
21. Krein SL, Kadri R, Hughes M, et al. Pedometer-based internet-mediated intervention for adults with chronic low back pain: randomized controlled trial. J Med Internet Res 2013;15:e181.
22. Du S, Liu W, Cai S, et al. The efficacy of e-health in the self-management of chronic low back pain: A meta analysis. Int J Nurs Stud 2020;106:103507.
23. Lee R, James C, Edwards S, et al. Evidence for the Effectiveness of Feedback from Wearable Inertial Sensors during Work-Related Activities: A Scoping Review. Sensors (Basel) 2021;21:6377.
24. Sandal LF, Stochkendahl MJ, Svendsen MJ, et al. An App-Delivered Self-Management Program for People With Low Back Pain: Protocol for the selfBACK Randomized Controlled Trial. JMIR Res Protoc 2019;8:e14720.
25. Sandal LF, Bach K, Øverås CK, et al. Effectiveness of App-Delivered, Tailored Self-management Support for Adults With Lower Back Pain-Related Disability: A selfBACK Randomized Clinical Trial. JAMA Intern Med

© Journal of Spine Surgery. All rights reserved.

2021;181:1288-96.
26. Hayden JA, Ellis J, Ogilvie R, et al. Exercise therapy for chronic low back pain. Cochrane Database Syst Rev 2021;9:CD009790.
27. Jalovaara P, Niinimäki T, Vanharanta H. Pocket-size, portable surface EMG device in the differentiation of low back pain patients. Eur Spine J 1995;4:210-2.
28. Brandt M, Madeleine P, Samani A, et al. Effects of a Participatory Ergonomics Intervention With Wearable Technical Measurements of Physical Workload in the Construction Industry: Cluster Randomized Controlled Trial. J Med Internet Res 2018;20:e10272.
29. Chandra S, Li J, Afsharipour B, et al. Performance Evaluation of a Wearable Tattoo Electrode Suitable for High-Resolution Surface Electromyogram Recording. IEEE Trans Biomed Eng 2021;68:1389-98.
30. Golabchi FN, Sapienza S, Severini G, et al. Assessing aberrant muscle activity patterns via the analysis of surface EMG data collected during a functional evaluation. BMC Musculoskelet Disord 2019;20:13.
31. Alsaadi SM, McAuley JH, Hush JM, et al. Assessing sleep disturbance in low back pain: the validity of portable instruments. PLoS One 2014;9:e95824.
32. Alsaadi SM, McAuley JH, Hush JM, et al. The bidirectional relationship between pain intensity and sleep disturbance/quality in patients with low back pain. Clin J Pain 2014;30:755-65.
33. Stone JD, Rentz LE, Forsey J, et al. Evaluations of Commercial Sleep Technologies for Objective Monitoring During Routine Sleeping Conditions. Nat Sci Sleep 2020;12:821-42.
34. Chen J, Abbod M, Shieh JS. Pain and Stress Detection Using Wearable Sensors and Devices-A Review. Sensors (Basel) 2021;21:1030.
35. Dobbins C, Fairclough S. Signal Processing of Multimodal Mobile Lifelogging Data Towards Detecting Stress in Real-World Driving. IEEE Trans Mob Comput 2019;18:632-44.
36. Meina M, Ratajczak E, Sadowska M, et al. Heart Rate Variability and Accelerometry as Classification Tools for Monitoring Perceived Stress Levels-A Pilot Study on Firefighters. Sensors (Basel) 2020;20:2834.
37. Torrente-Rodríguez RM, Tu J, Yang Y, et al. Investigation of cortisol dynamics in human sweat using a graphene-based wireless mHealth system. Matter 2020;2:921-37.
38. Rice P, Upasham S, Jagannath B, et al. CortiWatch: watch-based cortisol tracker. Future Sci OA 2019;5:FSO416.
39. Çelenay ŞT, Kaya DÖ, Özüdoğru A. Spinal postural training: Comparison of the postural and mobility effects of electrotherapy, exercise, biofeedback trainer in addition to postural education in university students. J Back Musculoskelet Rehabil 2015;28:135-44.
40. Cox ME, Asselin S, Gracovetsky SA, et al. Relationship between functional evaluation measures and self-assessment in nonacute low back pain. Spine (Phila Pa 1976) 2000;25:1817-26.
41. Steffens D, Ferreira ML, Latimer J, et al. What triggers an episode of acute low back pain? A case-crossover study. Arthritis Care Res (Hoboken) 2015;67:403-10.
42. van Dijk MJH, Smorenburg NTA, Heerkens YF, et al. Assessment instruments of movement quality in patients with non-specific low back pain: A systematic review and selection of instruments. Gait Posture 2020;76:346-57.
43. Straker LM, O'Sullivan PB, Smith A, et al. Computer use and habitual spinal posture in Australian adolescents. Public Health Rep 2007;122:634-43.
44. Kent PM, Keating JL, Taylor NF. Primary care clinicians use variable methods to assess acute nonspecific low back pain and usually focus on impairments. Man Ther 2009;14:88-100.
45. Foster NE, Anema JR, Cherkin D, et al. Prevention and treatment of low back pain: evidence, challenges, and promising directions. Lancet 2018;391:2368-83.
46. Vlaeyen JWS, Maher CG, Wiech K, et al. Low back pain. Nat Rev Dis Primers 2018;4:52.
47. Seid MA, Abdela OA, Zeleke EG. Adherence to self-care recommendations and associated factors among adult heart failure patients. From the patients' point of view. PLoS One 2019;14:e0211768.
48. Cholewicki J, Popovich JM Jr, Aminpour P, et al. Development of a collaborative model of low back pain: report from the 2017 NASS consensus meeting. Spine J 2019;19:1029-40.
49. Dunn KM, Campbell P, Jordan KP. Long-term trajectories of back pain: cohort study with 7-year follow-up. BMJ Open 2013;3:e003838.
50. Kongsted A, Kent P, Hestbaek L, et al. Patients with low back pain had distinct clinical course patterns that were typically neither complete recovery nor constant pain. A latent class analysis of longitudinal data. Spine J 2015;15:885-94.
51. Costa N, Smits E, Kasza J, et al. ISSLS PRIZE IN CLINICAL SCIENCE 2021: What are the risk factors for low back pain flares and does this depend on how flare is defined? Eur Spine J 2021;30:1089-97.
52. Suri P, Rainville J, de Schepper E, et al. Do Physical

© Journal of Spine Surgery. All rights reserved.

Activities Trigger Flare-ups During an Acute Low Back Pain Episode?: A Longitudinal Case-Crossover Feasibility Study. Spine (Phila Pa 1976) 2018;43:427-33.
53. Hurley DA, Murphy LC, Hayes D, et al. Using intervention mapping to develop a theory-driven, group-based complex intervention to support self-management of osteoarthritis and low back pain (SOLAS). Implement Sci 2016;11:56.
54. Jansen-Kosterink S, van Velsen L, Cabrita M. Clinician acceptance of complex clinical decision support systems for treatment allocation of patients with chronic low back pain. BMC Med Inform Decis Mak 2021;21:137.
55. Cholewicki J, Pathak PK, Reeves NP, et al. Model Simulations Challenge Reductionist Research Approaches to Studying Chronic Low Back Pain. J Orthop Sports Phys Ther 2019;49:477-81.
56. Zhang Y, Haghighi PD, Burstein F, et al. Electronic Skin Wearable Sensors for Detecting Lumbar-Pelvic Movements. Sensors (Basel) 2020;20:1510.
57. Costa N, Ferreira ML, Setchell J, et al. A Definition of "Flare" in Low Back Pain: A Multiphase Process Involving Perspectives of Individuals With Low Back Pain and Expert Consensus. J Pain 2019;20:1267-75.
58. Young AE, Wasiak R, Phillips L, et al. Workers' perspectives on low back pain recurrence: "it comes and goes and comes and goes, but it's always there". Pain 2011;152:204-11.
59. Levendowski DJ, Ferini-Strambi L, Gamaldo C, et al. The Accuracy, Night-to-Night Variability, and Stability of Frontopolar Sleep Electroencephalography Biomarkers. J Clin Sleep Med 2017;13:791-803.
60. Papi E, Bull AMJ, McGregor AH. Is there evidence to use kinematic/kinetic measures clinically in low back pain patients? A systematic review. Clin Biomech (Bristol, Avon) 2018;55:53-64.
61. Saraceni N, Kent P, Ng L, et al. To Flex or Not to Flex? Is There a Relationship Between Lumbar Spine Flexion During Lifting and Low Back Pain? A Systematic Review With Meta-analysis. J Orthop Sports Phys Ther 2020;50:121-30.
62. Swain CTV, Pan F, Owen PJ, et al. No consensus on causality of spine postures or physical exposure and low back pain: A systematic review of systematic reviews. J Biomech 2020;102:109312.
63. Lamoth CJ, Meijer OG, Wuisman PI, et al. Pelvis-thorax coordination in the transverse plane during walking in persons with nonspecific low back pain. Spine (Phila Pa 1976) 2002;27:E92-9.
64. Van Dillen LR, Gombatto SP, Collins DR, et al. Symmetry of timing of hip and lumbopelvic rotation motion in 2 different subgroups of people with low back pain. Arch Phys Med Rehabil 2007;88:351-60.
65. Mitchell T, O'Sullivan PB, Smith A, et al. Biopsychosocial factors are associated with low back pain in female nursing students: a cross-sectional study. Int J Nurs Stud 2009;46:678-88.
66. Tinitali S, Bowles KA, Keating JL, et al. Sitting Posture During Occupational Driving Causes Low Back Pain; Evidence-Based Position or Dogma? A Systematic Review. Hum Factors 2021;63:111-23.
67. Yip VY. New low back pain in nurses: work activities, work stress and sedentary lifestyle. J Adv Nurs 2004;46:430-40.
68. Needham R, Naemi R, Chockalingam N. Quantifying lumbar-pelvis coordination during gait using a modified vector coding technique. J Biomech 2014;47:1020-6.
69. Sparrey CJ, Bailey JF, Safaee M, et al. Etiology of lumbar lordosis and its pathophysiology: a review of the evolution of lumbar lordosis, and the mechanics and biology of lumbar degeneration. Neurosurg Focus 2014;36:E1.
70. Karayannis NV, Jull GA, Hodges PW. Physiotherapy movement based classification approaches to low back pain: comparison of subgroups through review and developer/expert survey. BMC Musculoskelet Disord 2012;13:24.
71. Dankaerts W, O'Sullivan P. The validity of O'Sullivan's classification system (CS) for a sub-group of NS-CLBP with motor control impairment (MCI): overview of a series of studies and review of the literature. Man Ther 2011;16:9-14.
72. Ganea R, Paraschiv-lonescu A, Aminian K. Detection and classification of postural transitions in real-world conditions. IEEE Trans Neural Syst Rehabil Eng 2012;20:688-96.
73. Atrsaei A, Dadashi F, Hansen C, et al. Postural transitions detection and characterization in healthy and patient populations using a single waist sensor. J Neuroeng Rehabil 2020;17:70.
74. Samson C, Koh A. Stress Monitoring and Recent Advancements in Wearable Biosensors. Front Bioeng Biotechnol 2020;8:1037.
75. Wang Z, Hao Z, Yu S, et al. A Wearable and Deformable Graphene-Based Affinity Nanosensor for Monitoring of Cytokines in Biofluids. Nanomaterials (Basel) 2020;10:1503.
76. Jayaraman A, Deeny S, Eisenberg Y, et al. Global position sensing and step activity as outcome measures of

© Journal of Spine Surgery. All rights reserved.

community mobility and social interaction for an individual with a transfemoral amputation due to dysvascular disease. Phys Ther 2014;94:401-10.
77. Reinertsen E, Clifford GD. A review of physiological and behavioral monitoring with digital sensors for neuropsychiatric illnesses. Physiol Meas 2018;39:05TR01.
78. Place S, Blanch-Hartigan D, Rubin C, et al. Behavioral Indicators on a Mobile Sensing Platform Predict Clinically Validated Psychiatric Symptoms of Mood and Anxiety Disorders. J Med Internet Res 2017;19:e75.
79. Chen W, Sabharwal A, Taylor E, et al. Privacy-Preserving Social Ambiance Measure From Free-Living Speech Associates With Chronic Depressive and Psychotic Disorders. Front Psychiatry 2021;12:670020.
80. Apkarian AV, Baliki MN, Farmer MA. Predicting transition to chronic pain. Curr Opin Neurol 2013;26:360-7.
81. van Tulder MW, Assendelft WJ, Koes BW, et al. Spinal radiographic findings and nonspecific low back pain. A systematic review of observational studies. Spine (Phila Pa 1976) 1997;22:427-34.
82. Zadro JR, Shirley D, Nilsen TIL, et al. Family History Influences the Effectiveness of Home Exercise in Older People With Chronic Low Back Pain: A Secondary Analysis of a Randomized Controlled Trial. Arch Phys Med Rehabil 2020;101:1322-31.
83. Denk F, McMahon SB, Tracey I. Pain vulnerability: a neurobiological perspective. Nat Neurosci 2014;17:192-200.
84. Dagostino C, De Gregori M, Gieger C, et al. Validation of standard operating procedures in a multicenter retrospective study to identify -omics biomarkers for chronic low back pain. PLoS One 2017;12:e0176372.
85. Shraim MA, Massé-Alarie H, Hall LM, et al. Systematic Review and Synthesis of Mechanism-based Classification Systems for Pain Experienced in the Musculoskeletal System. Clin J Pain 2020;36:793-812.
86. Shraim MA, Massé-Alarie H, Hodges PW. Methods to discriminate between mechanism-based categories of pain experienced in the musculoskeletal system: a systematic review. Pain 2021;162:1007-37.
87. Benditz A, Pulido LC, Grifka J, et al. A clinical decision support system in back pain helps to find the diagnosis: a prospective correlation study. Arch Orthop Trauma Surg 2021. [Epub ahead of print].
88. Mann NH 3rd, Brown MD. Artificial intelligence in the diagnosis of low back pain. Orthop Clin North Am 1991;22:303-14.
89. Boocock M, Naudé Y, Taylor S, et al. Influencing lumbar posture through real-time biofeedback and its effects on the kinematics and kinetics of a repetitive lifting task. Gait Posture 2019;73:93-100.
90. Anan T, Kajiki S, Oka H, et al. Effects of an Artificial Intelligence-Assisted Health Program on Workers With Neck/Shoulder Pain/Stiffness and Low Back Pain: Randomized Controlled Trial. JMIR Mhealth Uhealth 2021;9:e27535.
91. Fritsch CG, Ferreira PH, Prior JL, et al. TEXT4myBACK - The Development Process of a Self-Management Intervention Delivered Via Text Message for Low Back Pain. Arch Rehabil Res Clin Transl 2021;3:100128.
92. Chen M, Wu T, Lv M, et al. Efficacy of Mobile Health in Patients With Low Back Pain: Systematic Review and Meta-analysis of Randomized Controlled Trials. JMIR Mhealth Uhealth 2021;9:e26095.
93. Peake JM, Kerr G, Sullivan JP. A Critical Review of Consumer Wearables, Mobile Applications, and Equipment for Providing Biofeedback, Monitoring Stress, and Sleep in Physically Active Populations. Front Physiol 2018;9:743.
94. Girginov V, Moore P, Olsen N, et al. Wearable technology-stimulated social interaction for promoting physical activity: A systematic review. Cogent Social Sciences 2020;6:1. doi: 10.1080/23311886.2020.1742517
95. Seron P, Oliveros MJ, Gutierrez-Arias R, et al. Effectiveness of Telerehabilitation in Physical Therapy: A Rapid Overview. Phys Ther 2021;101:pzab053.
96. Beinart NA, Goodchild CE, Weinman JA, et al. Individual and intervention-related factors associated with adherence to home exercise in chronic low back pain: a systematic review. Spine J 2013;13:1940-50.
97. Sardi L, Idri A, Fernández-Alemán JL. A systematic review of gamification in e-Health. J Biomed Inform 2017;71:31-48.
98. Nicolson PJA, Hinman RS, Wrigley TV, et al. Effects of Covertly Measured Home Exercise Adherence on Patient Outcomes Among Older Adults With Chronic Knee Pain. J Orthop Sports Phys Ther 2019;49:548-56.
99. Sandal LF, Øverås CK, Nordstoga AL, et al. A digital decision support system (selfBACK) for improved self-management of low back pain: a pilot study with 6-week follow-up. Pilot Feasibility Stud 2020;6:72.
100. García Patiño A, Khoshnam M, Menon C. Wearable Device to Monitor Back Movements Using an Inductive Textile Sensor. Sensors (Basel) 2020;20:905.
101. Wu Y, Mechael SS, Carmichael TB. Wearable E-Textiles Using a Textile-Centric Design Approach. Acc Chem Res

© Journal of Spine Surgery. All rights reserved.

2021;54:4051-64.
102. Zaltieri M, Massaroni C, Lo Presti D, et al. A Wearable Device Based on a Fiber Bragg Grating Sensor for Low Back Movements Monitoring. Sensors (Basel) 2020;20:3825.
103. Howard J, Murashov V, Cauda E, et al. Advanced sensor technologies and the future of work. Am J Ind Med 2021. [Epub ahead of print].
104. Jeong YR, Lee G, Park H, et al. Stretchable, Skin-Attachable Electronics with Integrated Energy Storage Devices for Biosignal Monitoring. Acc Chem Res 2019;52:91-9.
105. Rong G, Zheng Y, Sawan M. Energy Solutions for Wearable Sensors: A Review. Sensors (Basel) 2021;21:3806.
106. de Arriba-Pérez F, Caeiro-Rodríguez M, Santos-Gago JM. Collection and Processing of Data from Wrist Wearable Devices in Heterogeneous and Multiple-User Scenarios. Sensors (Basel) 2016.
107. Razjouyan J, Lee H, Parthasarathy S, et al. Improving Sleep Quality Assessment Using Wearable Sensors by Including Information From Postural/Sleep Position Changes and Body Acceleration: A Comparison of Chest-Worn Sensors, Wrist Actigraphy, and Polysomnography. J Clin Sleep Med 2017;13:1301-10.
108. Slade P, Habib A, Hicks JL, et al. An open-source and wearable system for measuring 3D human motion in real-time. IEEE Trans Biomed Eng 2021. [Epub ahead of print].
109. Alonge F, Cucco E, D'Ippolito F, et al. The use of accelerometers and gyroscopes to estimate hip and knee angles on gait analysis. Sensors (Basel) 2014;14:8430-46.
110. van Dijk MP, Kok M, Berger MAM, et al. Machine Learning to Improve Orientation Estimation in Sports Situations Challenging for Inertial Sensor Use. Front Sports Act Living 2021;3:670263.
111. Wu LC, Nangia V, Bui K, et al. In Vivo Evaluation of Wearable Head Impact Sensors. Ann Biomed Eng 2016;44:1234-45.
112. Jiménez-Grande D, Farokh Atashzar S, Martinez-Valdes E, et al. Kinematic biomarkers of chronic neck pain measured during gait: A data-driven classification approach. J Biomech 2021;118:110190.
113. Richter C, King E, Falvey E, et al. Supervised learning techniques and their ability to classify a change of direction task strategy using kinematic and kinetic features. J Biomech 2018;66:1-9. Erratum in: J Biomech 2019;93:233.
114. Zemp R, Tanadini M, Plüss S, et al. Application of Machine Learning Approaches for Classifying Sitting Posture Based on Force and Acceleration Sensors. Biomed Res Int 2016;2016:5978489.
115. Smuck M, Odonkor CA, Wilt JK, et al. The emerging clinical role of wearables: factors for successful implementation in healthcare. NPJ Digit Med 2021;4:45.
116. Kim J. Analysis of health consumers' behavior using self-tracker for activity, sleep, and diet. Telemed J E Health 2014;20:552-8.
117. Hekler EB, Michie S, Pavel M, et al. Advancing Models and Theories for Digital Behavior Change Interventions. Am J Prev Med 2016;51:825-32.
118. Zhou M, Fukuoka Y, Goldberg K, et al. Applying machine learning to predict future adherence to physical activity programs. BMC Med Inform Decis Mak 2019;19:169.
119. Hasselgren A, Kralevska K, Gligoroski D, et al. Blockchain in healthcare and health sciences-A scoping review. Int J Med Inform 2020;134:104040.
120. Hill JC, Whitehurst DG, Lewis M, et al. Comparison of stratified primary care management for low back pain with current best practice (STarT Back): a randomised controlled trial. Lancet 2011;378:1560-71.

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