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Sensing behavior change in chronic pain: a scoping review of sensor technology for use in daily life

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Abstract

Technology offers possibilities for quantification of behaviors and physiological changes of relevance to chronic pain, using wearable sensors and devices suitable for data collection in daily life contexts. We conducted a scoping review of wearable and passive sensor technologies that sample data of psychological interest in chronic pain, including in social situations. Sixty articles met our criteria from the 2783 citations retrieved from searching. Three-quarters of recruited people were with chronic pain, mostly musculoskeletal, and the remainder with acute or episodic pain; those with chronic pain had a mean age of 43 (few studies sampled adolescents or children) and 60% were women. Thirty-seven studies were performed in laboratory or clinical settings and the remainder in daily life settings. Most used only 1 type of technology, with 76 sensor types overall. The commonest was accelerometry (mainly used in daily life contexts), followed by motion capture (mainly in laboratory settings), with a smaller number collecting autonomic activity, vocal signals, or brain activity. Subjective self-report provided "ground truth" for pain, mood, and other variables, but often at a different timescale from the automatically collected data, and many studies reported weak relationships between technological data and relevant psychological constructs, for instance, between fear of movement and muscle activity. There was relatively little discussion of practical issues: frequency of sampling, missing data for human or technological reasons, and the users' experience, particularly when users did not receive data in any form. We conclude the review with some suggestions for content and process of future studies in this field.

Keywords: Pain impact, Automated data collection, Wearable technology

1. Introduction

Pain functions to alarm for harm, enabling avoidance, escape, or withdrawal for recovery. Biological and psychological responses to pain or fear of pain can be measured at multiple levels, from the molecular to the behavioral. Capturing these changes requires multiple methodologies, and sensor-based digital technologies can provide information on, and analysis of, responses to pain. These technologies are continually improving in ease of use, methods of capture, and analysis, moving from the laboratory or clinic to the naturalistic environments that characterise daily life. Data capture in daily life, especially for sampling physiology, behavior, or self-report, is commonplace, and as technologies and their uses improve, they can be deployed passively without interference from participant awareness of measurement.

Existing reviews have quantified the benefits of technology to support exercise programmes,[53,92] improve broader outcomes of treatment,[55,92] or investigate use and preferences.[10] Some have addressed specific uses, such as sensor data to complement self-report by people in pain, summarized in 7 reviews for adults[13,53,55,75,92,93,98] and 1[10] in e-health interventions for children and young people. Three of these described the current state of wearable sensors in pain,[75,93,98] but only 1 used systematic search methods. Most reviews nominated pain intensity as the outcome of interest, overlooking other psychological and social aspects of pain experience, such as interference in daily life and social interactions. A few reviews mention emotions associated with pain experience, but only in passing,[55] or as contextual information for understanding pain intensity data.[75] Given the burgeoning use of technology in mental health research,[78] we were interested in the use of technology to investigate integral psychosocial aspects of pain. This scoping review addresses this gap by including relevant psychological and social constructs in our search, highlighting them in our results, and critically considering the implications of their use within our discussion.

This scoping review addresses the historical use of measurement technology assessing a broad range of pain-relevant psychological and social variables in dynamic real-world environments. In contrast to previously published reviews, we are also explicitly concerned with

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studies outside the laboratory, where every day people with pain face decisions and challenges without healthcare staff support. We are also concerned with the potential for data capture and analysis for use in determining states of chronic pain and transitions between those states.[22] We recognize that the impact of chronic pain is dynamic (fluctuating) and contextual[22]; measurement in the context where pain occurs, daily life, is an important extension of our inquiry. In fact, although some technologies are particularly suitable for application in both laboratory and community settings without degrading or voiding the experimental procedures, other technologies may present methodological and technical challenges preventing their application in daily life contexts.

2. Methods

The protocol was developed using the scoping review framework by Joanna Briggs Institute,[73] preregistered and available at the Open Science Framework (OSF), doi: 10.17605/OSF.IO/3CBDG.

2.1. Research questions

For sensors with potential application in daily life contexts and that sampled psychological and social data of interest in chronic pain, we aimed to

(1) map sensors by type;
(2) describe relationships between sensor data and psychological and social variables, clarifying assumptions linking measurement of an event or state to the sensor data ("ground truth");
(3) document practical limitations and strengths of the sensors or devices in relation to the measurement tasks and their contexts;
(4) document the research designs in which sensors or devices were applied; and
(5) identify sensor applications that are promising but understudied in pain.

2.2 Data sources and search strategy

2.2.1. Pilot search

With a view to capturing the full breadth of the use of sensors in studies of psychological and social variables, we ran a pilot search for studies with or without the term pain but with keywords related to disability. We then limited the search to those studies that included keywords related to psychological distress and to wearable technology compatible with home use. This first search yielded more than 10,000 results. One author (T.O.) screened these titles and then 3 authors (T.O., D.V., and A.W.) examined the results from the first title screening and decided that the search identified many titles that were (1) not directly concerned with pain or chronic pain and (2) focused exclusively on sensor feasibility without reference to any psychological or social constructs related to pain. This first search was therefore treated as a pilot search, and terms were revised for a new search that would include only pain or chronic pain studies that were also concerned with how sensor data related to existing psychological and social constructs related to pain.

2.2.2. Search strategy

PubMed, PsychINFO, and Web of Science publication databases were searched from inception to December 31, 2022, for published peer-reviewed articles meeting the criteria below. The search strategy applied the term "pain" in combination with keywords related to disability or movement difficulty, limiting studies to those that contained at least 1 from a list of terms related to psychological or social constructs and to any wearable or passive sensing technology compatible with home use (see search supplementary information, available at http://links.lww.com/PAIN/B973).

2.2.3. Inclusion criteria

We included all studies that recruited participants with either chronic pain or painful movement and that monitored at least 1 psychological or social variable. All included studies used 1 or more sensors (wearable or installed in the participant's house) to assess specific aspects of psychological (such as fear of movement or catastrophizing) or social (such as voice tone or count of social interactions) experiences related to pain.

2.2.4. Exclusion criteria

We excluded studies that did not explore (either qualitatively or quantitatively) any relationship between sensor data and other psychological or social aspects of pain (eg, fear of movement). In addition, for relevance to chronic pain, we excluded dental studies and any other studies (such as in surgical wards) where pain might be acute and activity was constrained. We excluded studies with sensors that could not be transferred to use in daily life contexts, such as requiring specialized laboratory settings or technology that required invasive procedures (eg, blood tests, implanted sensors). We excluded studies that were based on secondary data and articles in languages other than English.

2.3. Title and abstract screening

From the 3 data sources, the searches identified 3139 articles that were imported into EndNote 20 software[31] and deduplicated using DOI and then the EndNote 20 deduplication tool. This provided 2799 titles and abstracts. One author (T.O.) screened 461 titles from this updated search, and D.V. and A.W. screened the remaining 2338 new titles. D.V. and A.W. screened a random selection (10%) of titles screened by T.O. and calculated the ϕ reliability coefficient.[32] Similarly, D.V. and A.W. screened 10% of the titles allocated to each of them. The interrater reliability between A.W. and T.O. was $\phi = 0.80$, between D.V. and T.O. was $\phi = 0.84$, and between D.V. and A.W. was $\phi = 0.86$. All differences between reviewers were documented and resolved through consensus, leading to the inclusion of 1 article that had initially been excluded (refer to the PRISMA diagram).

2.3.1. Additional searches

The database searches yielded 37 reviews focused on pain, chronic pain, and wearable technology. The reference lists of these reviews were screened to identify further studies leading to the inclusion of 2 additional full texts. A total of 106 full texts were retrieved and examined (refer to the PRISMA diagram).

2.4. Full-text screening

Full texts were reviewed by a similar process. A.W. reviewed 23 of the 106 full texts and then reviewed an additional 15 titles that were randomly selected from those allocated to D.V. (n =83). Of the 15 full texts reviewed by both D.V. and A.W., 1 disagreement was resolved with the exclusion of 1 text. After the full-text review, the final list of full texts included was 60 (**Fig. 1**).

2.5. Data extraction

Two authors (T.O. and D.V.) extracted data, including title, year, author of publication, and key information about the sensors, how they were used, methods used to capture the experiences of interest from the sensor data, and relevant challenges reported for each technology (see supplementary information, available at http://links.lww.com/PAIN/B973).

3. Results

Consistent with accelerating trends in the availability and affordability of wearable sensors, 48.3% of the 60 studies included in this review were published between January 1, 2018, and December 31, 2022, with the remaining 31 covering a span of 23 years (**Table 1**). Most of the 60 studies (71.6%) were conducted either in Europe (38.3%) or in North America (33.3%), 16.6% in Asia, 5% in Australia, and 3.3% in South America and Middle East. Of the 23 European studies, 7 were from the United Kingdom, 3 from the Netherlands, and 2 from Germany. Of the 60 studies, 46 (76.6%) involved people with chronic pain and 14 recruited subjects with acute or other nonchronic pain presentations. Almost half of the selected studies (n = 28) involved people with back pain, and overall, we identified 11 general classifications of pain or chronic pain (**Fig. 2**), not mutually exclusive.

The average age of participants with chronic pain (weighted by sample size) was 43 (SD = 12) years, whereas that of participants with acute and nonchronic pain conditions was 51 (SD = 17) years. The proportion of female participants per chronic pain study (weighted by sample size) was 60.5% and 68.2% in the other studies. The proportion of men to women varied across the studies, with some that enrolled predominantly male or female participants (**Fig. 2**). Study design varied; 45% compared sensor users with a control group, 18.3% were longitudinal studies, and the remaining 33.3% were observational. More studies were conducted in laboratory or hospital settings (n = 37, 61.6%), and the remaining 38.3% (n = 23) were conducted in daily life contexts. Comparing these 2 types of settings, there was a significant difference in the proportion of the chosen research designs ($\chi^2(2) = 18.56$, $P < 0.01$); studies conducted in daily life settings were more likely to use longitudinal designs, where observational and controlled studies were more likely to be conducted in laboratory or hospital settings.

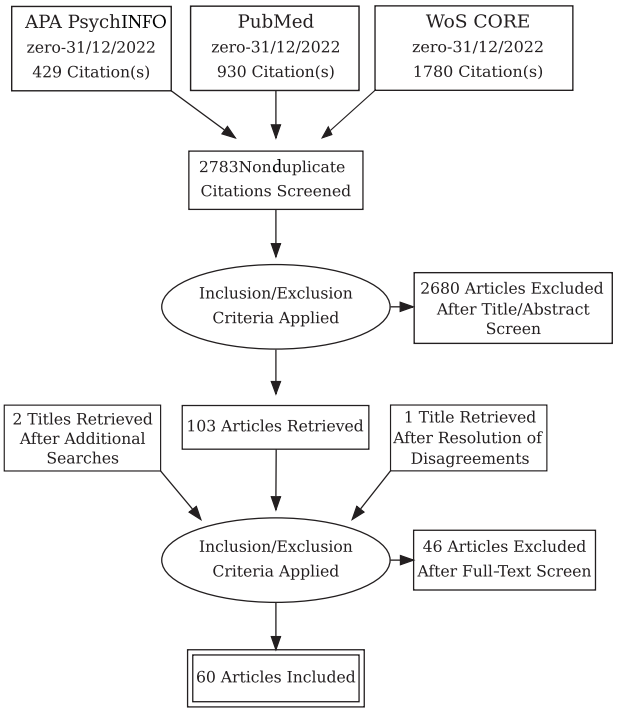

Figure 1. PRISMA diagram.

3.1. Sensor types

The 60 studies used 76 sensor units (average of 1.2 sensor per study), but most (n = 50, 65.8%) used only 1 type of technology. Many hospital-based and laboratory-based studies focused on measuring aspects of fine mobility in specific areas of the body (eg, the measure of angular velocity and range of trunk movements). These measures are most often achieved using 3D capturing systems, electrogoniometers, multiple inertial measurement units (IMUs), and virtual reality sets (**Fig. 3**). Eight sensor setups targeted muscle activity by electromyography (EMG), of which 7 were conducted in laboratory or hospital settings and only 1 study applied this technology in a naturalistic setting.[29]

Among the studies selected in this review, the use of sensing technology that captured fine whole-body kinematics appeared to be exclusively (n = 23) used in laboratory studies (**Fig. 3**). Similarly, all 6 sensor applications focused on gait and sway analysis were conducted in the laboratory using force platforms, IMUs, or 3D capturing systems. On the other hand, the studies conducted in daily life settings seemed less focused on fine local mobility with many examples of sensor applications (n = 15) using technologies that are less complex relatively to the previous group. These sensors were often low-power single-unit accelerometers such as step counter or other triaxial accelerometers that were used to measure activity levels and—in more recent studies—to recognize between a set of activities being engaged (eg, sleeping, resting, walking, or doing exercise). The studies focusing on psychological or social aspects of pain (eg, emotions or social interactions) were a minority (3/76), and they were all conducted in naturalistic settings using wearable cameras[95] or microphones.[74,96]

Autonomic activity was studied in both research contexts without notable differences (**Fig. 3**). The current selection of studies used heart rate sensors (n = 6) and respiratory sensors (n = 5), with 1 study using a wearable electroencephalogram (EEG)[8] and 1 study using a commercial smart bracelet to detect electrodermal activity.[52]

3.1.1. Movement and activity monitors

Motion sensor technology is used primarily as a method to quantify physical activity and to recognize activity patterns that represent differences in duration and type of activities. When used as a relative measure of physical activity, motion sensor data can be applied to indicate whether someone engages in light, moderate, or intense activity, or none. Activity data are often summarized on a daily basis, in some cases as a step count and in other cases unsupervised approaches are used to try to discriminate different patterns of activity throughout the day and quantify time spent in each (eg, sleeping, walking, or sitting down).

Although these metrics are good indicators of movement and general activity, their correlations with self-reported pain disability and pain intensity are inconsistent. For instance, evidence is inconsistent on the association between pain-related disability

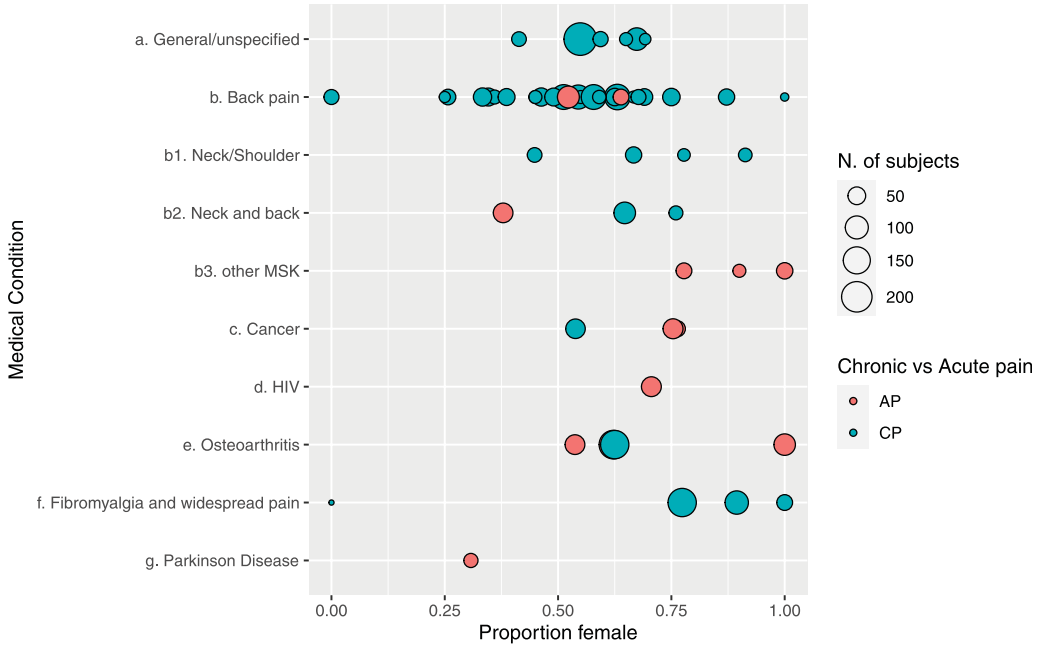

Figure 2. Schematic of sample representing pain type, medical condition, sample size, and sex across the extracted studies. The size of the coloured dots is proportional to the number of participants in that category. AP, acute pain; CP, chronic pain; MSK, musculoskeletal pain.

and direct measures of activity using motion sensors,[11,33,90] and between daily activity data and pain intensity (high correlation[35,36,40]; low correlation[11,17,33,42,60,90]). Reduced activity is associated with greater psychological symptomatology related to pain (such as fear of movement[89] or depression[47]) in some studies, but not others.[60] These studies applied different technologies, different sensor-to-participant setups, and made different pragmatic assumptions about how physical activity might be related to sensor data.

In addition, interpretation of motion data may require contextual information to make meaningful discriminations.[34] For instance, a pain-free individual and another with chronic pain may record the same volume of daily activity, but with different patterns: people with chronic pain in 1 study were very active in the mornings, followed by—perhaps necessitating—rest for most of the rest of the day, whereas participants without pain tended to be more active in the evening than in the morning.[36] Where the sensors do not give a timeline, participants may be prompted to record contextual information[4] or equipped with a wearable camera with sensors to record motion data with snapshots at regular intervals through the day, supplying social and interpersonal contexts.[95]

The technological complexity of motion sensors varies considerably between studies, from a wrist-worn step counter to multiple motion sensors capturing detailed information about posture and bodily movement.[6] In the following paragraphs, we

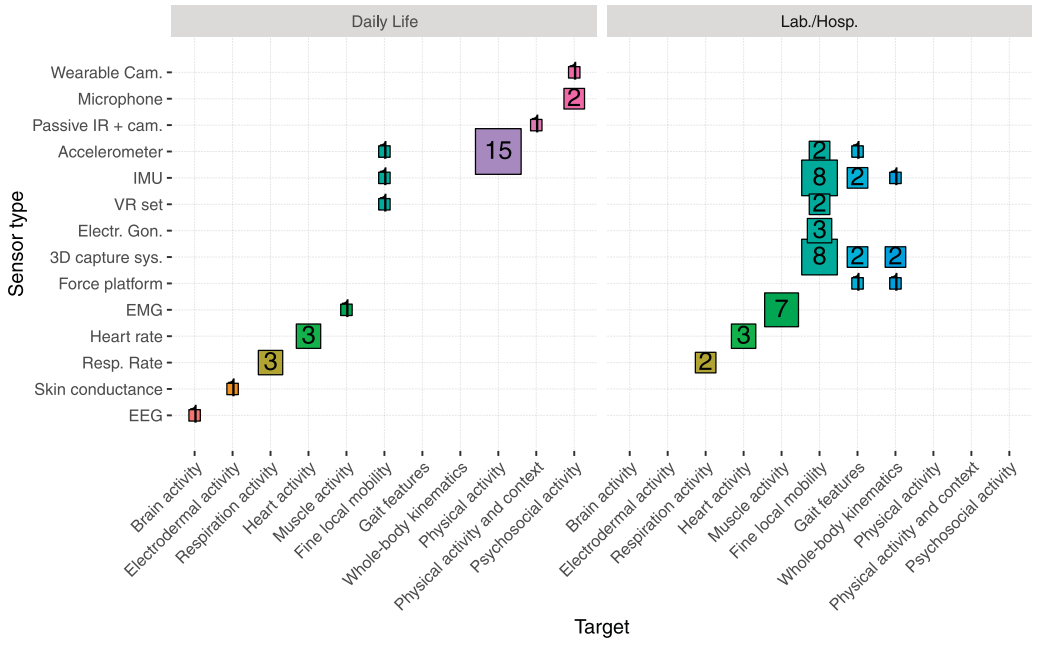

Figure 3. Graphical contingency tables showing the frequency of sensor types by target of measurement and research context.

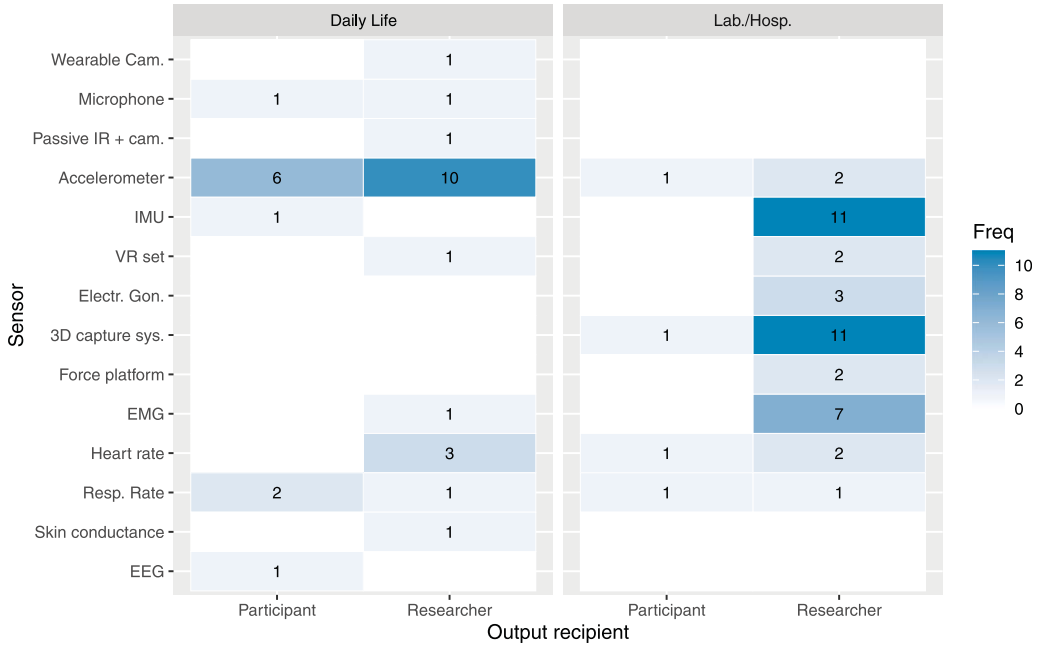

Figure 4. Heatmap of sensor use by setting, showing frequency of output of a sensor aimed at researcher or participant. EEG, electroencephalogram; Electr. Gon., electronic goniometer; EMG, electromyogram; IMU, inertial motion unit; IR, infrared; VR, virtual reality.

focus on studies that used sensor setups focused on capturing fine features of movement such as range of movement (ROM), velocity of movement (eg, angular velocity), balance and coordination (eg, gait analysis), or other specific characteristics of movement such as hesitation, guarding, or facial expressions.

This subgroup of studies is characterized by a general heterogeneity of the methods used to elicit motion across studies, with some studies instructing participants to perform tasks as fast as possible, some inviting them to move at a comfortable pace, and others that gave no specific instructions. These differences in the pace of the tasks can affect the outcomes of the different kinematic measures.[86] In the studies focused on neck pain, changes in neck ROM, angular velocity, or both were related to pain intensity[1,52,77,88] and in some cases also to pain-related disability.[1,77,88] In studies of spinal, trunk, or lumbar mobility, there is at best weak evidence of a relationship between ROM or angular velocity and pain intensity[26,27,48,71,90]; the same holds between those kinematic measures and pain-related disability.[3,15,48,54,72] Three-dimensional motion detection systems that can identify and track the position of multiple specific markers placed on the body to record 3-dimensional characteristics of movement are used to detect and monitor changes in (eg,) dynamics of walking or standing up or sitting down.

Results of these studies in relation to psychological characteristics are mixed: some suggest that gait and posture are related to self-reported pain, depression and anxiety,[51] and fear of movement,[7,18,65] but others suggest no relationship.[48,91] Relationships found between movement kinematics and fear seemed somewhat stronger,[7,19,52,79] but not for the relationship between ROM and fear of movement (typically measured by the Tampa Scale of Kinesiophobia [TSK][58]) in back pain[41,48,71,91] and neck pain.[1,3,88] Task-specific fear might be expected to be more closely related to performance than broader fear of movement.[38] In addition, there is some evidence that movement velocity captures kinematic features affected by fear of movement better than do displacement and ROM measures,[39,64,72,86] with longer time of movement execution associated with fear of movement.[70,72] A recent virtual reality study using both headset and handheld sensors found changes in movement velocity to be associated with both fear of movement and reinjury and chronic low back pain.[52] This may not be due to slowed movement so much as alternative joint coordination choices[86] and stops and hesitation in movement[94] (associated with fear of movement[39,67,71]). The relationship between fear and movement detection seems stronger when the fear of movement is measured in relation to the movement task[26,27,38] rather than the total TSK score[38,54] or pain-related anxiety[85] rather than general anxiety.[46,90]

3.1.2. Autonomic activity

This group of 13 sensors included 6 for monitoring cardiovascular activity, their complexity ranging from infrared (IR) pulse oximeters sampling blood oxygenation and heart rate to multitrace electrocardiograms (ECGs). Heart rate variability (HRV) data were used to monitor autonomic regulation and to assess autonomic sympathetic vs parasympathetic balance.[9,23,35,36] Heart rate variability data can also be used in biofeedback devices that aim to support the promotion of normal cardiorespiratory homeostasis.[9] Reductions in HRV can indicate underlying autonomic dysregulation associated with persistent pain.[9,23,34] Comparing chronic pain with healthy controls, participants with pain show a dominance of the sympathetic system such that "fight or flight" states prevail over a parasympathetic response that would promote relaxation and resting.[23,34,36] Diminished parasympathetic activation at night has been associated with sleep disturbance and decreased physical activity.[35] The same authors suggest that decreased physical activity may contribute to worse pain symptoms through autonomic nervous system (ANS) changes,[35,36] but changes in ANS regulation detected through monitoring of HRV levels alone do not seem to be associated with self-reported anxiety,[23] stress,[35,36] or quality of life.[34] In the case of fibromyalgia (FM), 1 study suggested that the dissociation between change in self-reported symptoms and ANS responses may indicate that the latter constitute a primary trait of FM.[34]

Table 1

Title and short description of studies.

Author year	Design	Research context	Pain-related condition	Type of sensor	Data available	Age category	Sample size (pain gr.)	Attrition rate	Mean age*	Age SD*	N. Female
Alalawi 2022[1]	Controlled	Lab./Hosp.	b1. Neck/Shoulder	IMU	No info provided	Adults	18	0.00%	38.7	12	14
Alberts 2020[2]	Controlled	Daily life	c. Cancer	Resp. rate	Unclear	Adults	65	3.08%	44.1	8.7	35
Alcaraz 2021[3]	Controlled	Lab./Hosp.	b2. Neck and low back	IMU	No info provided	Adults	66	0.00%	40.35	13.08	25
Alschuler 2011[4]	Longitudinal	Daily life	b. Back pain	Accelerometer	No info provided	Adults	20	0.00%	46.1	9.35	9
Aung 2016[6]	Controlled	Lab./Hosp.	b. Back pain	IMU, EMG, 3D capt.	On request	Adults	22	0.00%	50.5	14.6	15
Beebe 2021[7]	Observational	Lab./Hosp.	a. General/unspec.	3D capture system	No info provided	Children	16	15.00%	13.8	2.2	13
Birch 2022[8]	Observational	Daily life	a. General/unspec.	EEG	On request	Adults	29	44.83%	50.2	—	12
Burch 2020[9]	Controlled	Lab./Hosp.	c. Cancer	Heart—HR/V	No info provided	Adults	38	10.53%	60	3	39
Carvalho 2017[11]	Longitudinal	Daily life	b. Back pain	Accelerometer	No info provided	Adults	130	8.46%	39.1	11.2	82
Cooper 2017[14]	Controlled	Daily life	e. Osteoarthritis	Accelerometer	No info provided	Adults	67	7.46%	60.5	10.3	36
Davis 2013[15]	Observational	Lab./Hosp.	a. General/unspec.	IMU	No info provided	Adults	235	5.11%	32	—	129
de Groot 2008[17]	Controlled	Daily life	e. Osteoarthritis	Accelerometer	No info provided	Adults	84	0.00%	61.7	11	84
de Oliveira Silva 2019[18]	Observational	Lab./Hosp.	b4. other MSK	3D capture system	No info provided	Adults	40	0.00%	22.23	3.2	40
Devecchi 2022[19]	Observational	Lab./Hosp.	b1. Neck/Shoulder	IMU	No info provided	Adults	85	0.00%	33.3	9.4	55
Dubois 2014[21]	Controlled	Lab./Hosp.	b. Back pain	EMG	No info provided	Adults	52	0.00%	39.8	11.5	18
Evans 2013[23]	Controlled	Lab./Hosp.	b. Back pain	Heart—HR/V	No info provided	Children	48	12.50%	14.2	2.6	30
Fujii 2022[26]	Controlled	Lab./Hosp.	b. Back pain	3D capture system	On request	Adults	31	0.00%	30.5	5.2	0
Fujii 2021[27]	Observational	Lab./Hosp.	b. Back pain	3D capture system	On request	Adults	35	0.00%	30	Range	9
Geisser 1995[29]	Longitudinal	Daily life	b. Back pain	EMG	No info provided	Adults	25	16.00%	35.1	—	9
Greenberg 2020[33]	Longitudinal	Daily life	a. General/unspec.	Accelerometer	No info provided	Adults	95	16.84%	50.7	14.7	64
Grossman 2016[34]	Controlled	Daily life	f. Fibromyalgia, CRPS, WSP	HR/V, RR, acc.	No info provided	Adults	168	22.62%	54.1	9.1	130
Hallman 2012[36]	Controlled	Daily life	b1. Neck/Shoulder	Heart—HR/V, accel.	No info provided	Adults	23	17.39%	40.5	7.1	21
Hallman 2014[35]	Controlled	Daily life	b1. Neck/Shoulder	Heart—HR/V, accel.	No info provided	Adults	29	6.90%	41	10	13
Imai 2022[38]	Observational	Lab./Hosp.	b. Back pain	3D capture system	No info provided	Adults	54	0	47.1	11.1	25
Imai 2022[39]	Longitudinal	Lab./Hosp.	b3. other MSK	Accelerometer	No info provided	Adults	20	0.00%	69.7	10.2	18
Jacobson 2021[40]	Longitudinal	Daily life	f. Fibromyalgia, CRPS, WSP	Accelerometer	Public	Adults	68	—	41.3	8.1	48
Jette 2016[41]	Observational	Lab./Hosp.	a. General/unspec.	IMU	No info provided	Adults	32	0.00%	32.9	7.83	19

(*continued on next page*)

Table 1 (*continued*)

Author year	Design	Research context	Pain-related condition	Type of sensor	Data available	Age category	Sample size (pain gr.)	Attrition rate	Mean age*	Age SD*	N. Female
Kashikar-Zuck 2010[42]	Longitudinal	Daily life	f. Fibromyalgia, CRPS, WSP	Accelerometer	No info provided	Children	104	0.00%	14.9	1.8	93
Kent 2015[43]	Controlled	Daily life	b. Back pain	IMU	On request	Adults	112	24.11%	39	12	61
Khan 2022[44]	Observational	Lab./Hosp.	b. Back pain	IMU	No info provided	Adults	121	0.00%	55	10	62
Kim 2017[45]	Longitudinal	Daily life	a. General/unspec.	Camera + PIR*	No info provided	Elderly	20	0.00%	—	—	—
Knox 2006[46]	Controlled	Lab./Hosp.	b1. Neck/Shoulder	Electrogoniometer	No info provided	Adults	9	0.00%	39	9	7
Korszun 2002[47]	Controlled	Daily life	f. Fibromyalgia, CRPS, WSP	Accelerometer	No info provided	Adults	22	0.00%	48	3	24
Lamoth 2006[48]	Controlled	Lab./Hosp.	b. Back pain	3D capture system, EMG	No info provided	Adults	22	13.64%	38	—	13
Lewis 2012[50]	Controlled	Lab./Hosp.	b. Back pain	EMG	No info provided	Adults	42	9.52%	46.2	11.1	29
Liguori 2021[51]	Observational	Lab./Hosp.	n. Parkinson Dis.	IMU	No info provided	Adults	26	0.00%	65.4	8.7	8
Liikkanen 2022[52]	Controlled	Daily life	b. Back pain	VR set, EDA, acc.	On request	Adults	39	0.00%	54.7	—	34
Matheve 2018[54]	Controlled	Lab./Hosp.	b. Back pain	IMU	On request	Adults	54	18.52%	43	12	18
Mora 2012[59]	Controlled	Lab./Hosp.	b3. other MSK	EMG	No info provided	Adults	36	7.69%	27.4	6.8	28
Murphy 2013[60]	Longitudinal	Daily life	e. Osteoarthritis	Accelerometer	No info provided	Adults	172	18.60%	72	6	107
Nijs 2008[62]	Observational	Lab./Hosp.	f. Fibromyalgia, CRPS, WSP	HR/V, resp. rate	No info provided	Adults	36	0.00%	39	8	36
Nishi 2022[64]	Controlled	Lab./Hosp.	b. Back pain	Force plat., Elect. Gon.	No info provided	Adults	48	0.00%	54.46	13.08	36
Nishi 2021[65]	Controlled	Lab./Hosp.	B. Back pain	Accelerometer	No info provided	Adults	20	0.00%	54.05	10.76	9
Nordstoga 2019[67]	Longitudinal	Lab./Hosp.	B. Back pain	IMU	No info provided	Adults	44	31.82%	45.1	14.7	17
Osumi 2018[70]	Observational	Lab./Hosp.	f. Fibromyalgia, CRPS, WSP	3D capture system	Unclear	Children	1	0.00%	13	—	—
Osumi 2019[71]	Controlled	Lab./Hosp.	B. Back pain	Electrogoniometer	No info provided	Adults	45	0.00%	56.23	10.61	
Ozcan Kahraman 2018[72]	Observational	Lab./Hosp.	b. Back pain	Force platform	No info provided	Adults	51	0.00%	39	—	25
Reinen 2022[74]	Observational	Daily life	b. Back pain	Acc., microphone	No info provided	Adults	121	4.13%	59.4	—	70
Sarig Bahat 2014[77]	Observational	Lab./Hosp.	b1. Neck/Shoulder	VR set	No info provided	Adults	25	0.00%	39	12.7	19
Singh 2016[80]	Observational	Lab./Hosp.	b. Back pain	Acc., resp. rate	No info provided	Adults	15	—	—	—	10
Singh 2017[79]	Observational	Daily life	b. Back pain	Accelerometer	No info provided	Adults	4	0.00%	—	—	4
Svendsen 2013[83]	Controlled	Lab./Hosp.	b. Back pain	EMG	No info provided	Adults	12	0.00%	38.6	9.8	3
Thomas 2007[85]	Observational	Lab./Hosp.	b. Back pain	3D capture system	No info provided	Adults	36	0.00%	26.85	6.68	23

(*continued on next page*)

Table 1 (*continued*)

Author year	Design	Research context	Pain-related condition	Type of sensor	Data available	Age category	Sample size (pain gr.)	Attrition rate	Mean age*	Age SD*	N. Female
Thomas 2008[86]	Observational	Lab./Hosp.	b. Back pain	3D capture system	No info provided	Adults	88	0.00%	30.9	10.3	46
Treleaven 2016[88]	Observational	Lab./Hosp.	b1. Neck/Shoulder	VR set	No info provided	Adults	39	0	41.56	12.73	26
Uritani 2020[89]	Observational	Daily life	e. Osteoarthritis	Accelerometer	On request	Adults	168	0.00595	62.2	7.5	105
Vaisy 2015[90]	Controlled	Lab./Hosp.	b. Back pain	IMU	No info provided	Adults	20	0.00%	32.9	9.6	11
Veeger 2020[91]	Observational	Lab./Hosp.	b. Back pain	3D capt., EMG	No info provided	Adults	31	0.00%	33	—	21
Wilson 2018[95]	Controlled	Daily life	a. General/unspec.	Wearable camera	No info provided	Adults	13	7.69%	70	—	9
Wright 2021[96]	Observational	Daily life	c. Cancer	Microphone	Public	Adults	56	8.70%	56	14	52

* In the studies examining more than 1 pain group, means are "combined means" and SDs are "pooled SDs."
CRPS, complex regional pain syndrome; EEG, electroencephalogram; EMG, electromyography; HR/V, heart rate variability; IMU, inertial measurement units; MSK, musculoskeletal pain; RR, respiratory rate; VR, virtual reality.

Respiratory monitors detect ventilation volume, breathing rate, and breathing rate patterns throughout the day by sensing changes in the expansion and contraction of the rib cage. These data can be used to indicate relative states of calm or stress[2] and can be fed back to the wearer.[2] Respiratory rate data can be augmented using synchronous heart rate and movement data improving the clinical relevance of the autonomic measures and discriminating between healthy participants and participants with chronic pain.[34] Heart rate sensors in combination with respiratory monitors and oximeters can be used to monitor functional aerobic impairment. One study that focused on measuring peak heart rate and peak oxygen consumption during intense exercise found that high levels of both were negatively correlated with pain catastrophizing and positively correlated with pain intensity.[62]

3.1.3. Voice data processing

Voice recordings can be used to capture descriptions of the experience of pain, but newer analytical techniques (eg, artificial intelligence) can recognize signs of emotional states in speech features such as voice tone and speech richness.[74] Similarly, sound files containing clues to social interactions can be coded and analysed to detect the frequency and length of conversations, for instance, about pain. A recent study of social interactions using the method to monitor disclosure of pain to significant others or to other social networks showed that most conversations about pain involved people *outside* the closest circle of significant others.[96]

3.1.4. Muscle activity

Electromyographic sensors detect and measure muscle activity local to their position on the body; they are often used to measure muscle contractions (with or without movement), and in some cases, they are interpreted as pain-related behaviors. Depending on the specific aim of the study, EMG data are used to monitor muscle recruitment at rest, during activity, or throughout the day to study muscle activation intensity and maintenance (eg, prolonged muscle tension), and muscle recruitment patterns in particular areas of interest, with the expectation of certain muscle activity patterns or greater contraction intensity to be associated with greater pain and disability.50,62 When considered in relation to physical activity, muscle recruitment should be interpreted with caution because muscle recruitment may occur without observable physical activity.[29]

In some studies, EMG, accelerometer, and gyroscope data were combined to study muscle activity in relation to posture or to specific body or joint kinematics.[6,46] Electromyography data can also be used to determine the presence of dysfunctional neuromuscular adaptations associated with self-reported disability[21] or to associate muscle recruitment patterns with specific pain behaviors (eg, protective posture).[6] In the included studies, the evidence on association between EMG data and fear of pain was somewhat contradictory[48,50,91]; in some but not all studies, EMG data were correlated with pain-related anxiety,[50] catastrophizing, and "ignoring pain sensation."[83] Electromyography data were investigated in relation to broader psychological variables such as depression or general anxiety but not consistently related to them.[29,50,59]

Table 2

Technological challenges reported in daily life and laboratory settings.

Type of challenge	Daily life settings N	Laboratory settings N
Forgetting/refusing to wear/use	7	0
Needing charge	2	0
Putting it on	4	0
Discomfort	4	0
Inconvenience	3	1
Inaccuracy	3	1
Difficulty keeping in place	3	0
Needing user engagement	1	0
Corrupted or missing data	4	6
Total	31	8

Table 3

Count of predicted* vs observed reports of zero attrition.

	Predicted as zero	Predicted as non-zero
Observed as zero	31	5
Observed as non-zero	13	11

* This logistic model analysed sample size and research context as independent predictors of the probability of observing study attrition as zero.

3.1.5. Brain activity

We found only 2 studies that applied a portable EEG in the context of acute or chronic pain and where the EEG device was completely managed by participants. In both cases, the EEG sensor units were part of a wearable interface that livestreamed brain activity for neurofeedback. This specific use case allows control of some crucial aspects of the EEG recording session (ie, participant static in a room with constant lighting and following precise instructions on a computer screen). However, only 1 study[8] discussed EEG data in relation to psychological or social variables, and in this case, theta (4–8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and hi-beta (20-30 Hz) frequency bands were used for biofeedback. Decreased activity in relative hi-beta was associated with decreased anxiety and depression levels.

3.1.6. Multidimensional data

Some studies have started to explore the use of different synchronous sources of data from sensors in the context of pain. For example, using cameras, EMGs, and multiple motion sensor units, it is possible to use AI to systematically detect emotional states associated with facial expressions, as well as detecting pain-related behaviors (eg, guarding or limping) associated with specific body postures, movement velocity, and movement patterns.[6] AI algorithms may be used with an array of unobtrusive sensors installed in the target's environment to detect and analyse motion and behavioral patterns associated with depression and with difficulties in activities of daily living.[45] The combined measures of autonomic functioning with measures of physical activity can provide context to improve the clinical relevance of these measures.[34] Another study used multiple input streams to represent changes in pain states over time, with sensors recording both actigraphy and speech, then combining these data with questionnaires on sleep quality, mood, alertness, pain intensity, activities of daily living (ADLs), and medication use.[74]

Multiple sensor inputs can be transformed into intelligible feedback to wearers. Real-time sensor data was translated into sound feedback (sonification) to enhance the wearer's capacity to explore and extend movement patterns,[79,80] with feedback associated with improved awareness of and confidence in movement.[79] Another therapeutic development was the combination of EMG and motion activity data to detect associations between pain and posture, fed back to the wearer to support retraining of movement.[43]

3.2. Researcher-oriented vs user-oriented output

Although researchers always obtained raw or processed data, there was considerable variability in whether user participants received any data at all, despite the opportunities for user experience to refine design and the possible therapeutic feedback to users. **Figure 4** shows twin heatmaps indicating who received data: in most laboratory and hospital applications (41/45), the output of the technology was unavailable to participants. A similar trend can be observed in naturalistic settings, although most of the sensors that provided a readable output to the participants were sensors detecting and measuring the volume of activity (eg, step count). The 2 contexts of study seemed almost complementary, with some technologies being applied almost exclusively in daily life settings.

3.3. Attrition and technology challenges

Technological problems and other sources of missing data are shown in **Table 2**; 24 (36.6%) of the 60 studies provided information about the practical challenges encountered. Most of the challenges (31/39) were reported in studies conducted in daily life settings with some of the challenges begin reported exclusively in this context, such as "forgetting or refusing to attach sensors,", "needing to recharge," and "putting it on."

In more than half the studies (20/39), sensor data were missing or corrupted (10/39), participants forgot or refused to wear devices (7/39), or found them uncomfortable (4/39). In a few cases, data accuracy was inadequate (4/39), rendering data unusable.

We tried to extrapolate attrition due to technology vs to any other cause, but most (36/60) studies gave too little detail of attrition rates, particularly those studies conducted in laboratory or hospital settings (28/36). Overall, the average attrition rate weighted by sample size was 0.07 (weighted SD = 0.08). Most (36/42) studies that reported zero attrition were in controlled settings and often for relatively short times. We used 2 logistic models to analyse the relationship between sample size and context of study on the probability of study attrition of zero. One model showed that as sample size increased by 1 unit, the log odds of observing attrition equal to zero decreased by −0.019 ($P = 0.009$). A second model combining both predictors showed that both sample size (coeff = −0.015, $P = 0.037$) and laboratory or hospital research contexts (coeff = 1.278, $P = 0.041$) were independent significant predictors of zero attrition. This second model presented a better fit with a lower Akaike information criterion parameter in comparison with that using sample size as a sole predictor of zero attrition (**Table 3**) and did so with acceptable sensitivity (0.70) and specificity (0.68).

4. Discussion

Our search for wearable or fixed sensors useable in the environment of people with pain, focusing on psychological and social variables, provided 60 studies, mainly on musculoskeletal pain[16,20,49,63] and in high-income countries. Most were conducted in the 5 years preceding the search, benefiting from rapid technological progress. Just under 40% were conducted in daily life settings rather than laboratory or hospital, but all sensors could potentially be used by participants in daily life.

The largest number of studies was of cumulative physical activity using accelerometers. Activity is an important outcome in rehabilitation of painful conditions, and technology complements self-report. Studies differed in how to summarize sensor data and how often to sample it, whereas interpretation of some sensor data seemed to make substantial assumptions about what was (and was not) relevant contextual information. Movement studies also used detailed sensor quantification of *muscle activity*, mostly in single session laboratory or clinic settings, although context and information from additional sensors was underused in exploring gross movement in space. The influences of psychological and pain factors on movement were considered, but often corresponded poorly with sensor data. Heart rate was also a common target; wrist-worn devices are widely available, relatively low cost, and acceptable,[30] but interpretation of findings often lacked a theoretical basis. Studies reviewed here confirm that HRV monitoring can indicate a shift toward sympathetic predominance of the ANS in chronic pain,[23, 34–36] but there seems to be no relation between HRV and stress or anxiety.[23,35,36] Interpretation is hampered by lack of clarity on the causal direction of these relationships and on whether and how psychological and social factors interact with the ANS.

Electroencephalogram was the only brain imaging technology that met our search criteria. We found no pain studies involving the

use of near-infrared spectroscopy in daily life contexts.[87] Various EEG devices are available in small, wearable, battery-powered, and wireless brain–computer interfaces (BCIs),[12] but few are plug-and-play devices.[97] The technology has critical limitations for use in community settings, including poor signal detection on the scalp, degrading spatial resolution[5,12]; compromise between number of sensors and memory and power requirements[56]; and data artefacts from extraneous signals.[57] There are also unresolved questions of ground truth for psychological states.[5]

In sensor data validation, "ground truth" refers to a reliable reference point—a valid analogue—for interpreting and evaluating its accuracy. Addressing this challenge is crucial as certain health-related constructs, such as activity or emotional states, are hard to quantify. In using sensor data to infer mental or emotional states, establishing ground truth is particularly challenging because it relies on self-reports that are themselves subject to bias.[28] As the potential of sensor capture, computing power, and data availability increases exponentially over time, assessing content validity is crucial to understand how sensor data relate to health status. In fact, sensor data used to infer mental states, such as social withdrawal in depression, relies both on measurement accuracy and understanding of measurement error, and on a theoretical context to make sense of behavior,[84] both lacking in pain.

Extending the number of variables captured risks exacerbating unresolved problems. Many studies reviewed communicated little on relevant technical and practical problems in daily life settings, but data interpretation is compromised by large quantities of missing data because of connection or charging problems or intentional or inadvertent nonuse. Willingness to wear a device may be enhanced by comprehensible feedback, but few took the user perspective to understand how sensors could serve and support everyday life,[79,80] in contrast to the mental health field, where many sensor-based apps interact directly with the user and (with consent) transmit data to the clinical team.[24]

We supplemented our search by exploring use of sensors and wearables in mental health research. Two reviews described strengths and shortcomings,[37,78] particularly the scarcity of studies focused on daily life contexts. Some stress studies were relevant, assessing stress by cortisol detection in sweat[76]; photoplethysmographic methods with sensors on fingers, wrist, or earlobe[61]; and smartphone applications for analysing speech, where changes in muscle tension and breathing affecting speech prosody are reasonably well correlated with skin conductance parameters.[81] The use of voice features to indicate psychological disorders is a burgeoning area,[78] as are social contact factors to indicate depression.[37] However, authenticating data labels for relevant mood states remains problematic, and few studies address clinical utility. Recommendations emphasize greater involvement of experts by experience in development and testing and multiple sensor use to improve accuracy.[61]

Also of relevance to pain studies is the growing interest in interoceptive awareness and its relevance for mental representation and interpretation of bodily states and experiences. This has focussed mainly on psychological disorders, exploring factors such as oxygen consumption, thermoregulation, and acoustic feedback related to heart rate during exertion.[66,82] Despite these efforts, universally applicable and measurable bodily indicators for core emotions are not yet established.

4.1. Gaps, strengths, and limitations

Apart from the restricted range of technology used in pain compared with other disorders, our review revealed important gaps. One was the underrepresentation of different chronic pain conditions. For example, people with disorders such as chronic pelvic or visceral pain may wish to track symptoms, activities, food intake, or stress. Sensor research studies could potentially support self-management of these conditions and enrich clinical care with deeper understanding of fluctuations ("flares"). Children and adolescents were underrepresented, despite the relevance of questions asked in adult studies to younger people with pain. There was limited geographical diversity, with few studies from Asia and none from South America or Africa. Our search limit to articles in English may have partially contributed to this, although differences in culture, digital ubiquity, and national health priorities are likely also relevant factors. Diversity in study populations offers better understanding of pain experience and healthcare needs, but substantial differences in practicality of healthcare solutions (technological or otherwise) exist between rich, industrialized regions and lower resource regions.

Despite the recency of many studies, open science practices, including publishing protocols and data sharing, were rarely described. Given the effort and expense of collecting these data, data sharing is important.[68] Nor were issues of data storage, security, and privacy of identifiable data much discussed. We have not addressed here technological monitoring of individuals' behavior, even of their physiology, with or without consent, as instituted for benign reasons to detect lack of motion in homes of elderly people living alone.

4.2. Ways forward

Ground truth, information independent of the sensor/s that enables interpretation of sensor data, often relies on self-reports that are inevitably subject to various sources of error and inaccuracy.[28] Few studies addressed this problem or issues of clinical relevance and importance of different scales of description, such as steps or day vs lumbar muscle activity to quantify function. Self-reported physical functioning, muscle activation, and step count are complementary representations of functional ability rather than interchangeable.[14,17]

Good practice encourages the involvement of multiple stakeholders, particularly those with relevant experience. Contributions from end users were rare, and only 7 of the 60 studies shared their findings with participants. Discussion of our findings with experts by experience raised novel issues, such as feedback from sensors boosting motivation for challenging activities and learning new ways to control pain. Although rarely addressed in pain self-management, variability in pain could, in principle, inform decisions about balance and timing of activity and rest. People with chronic pain also reminded us that medication, including side effects, can enable or undermine activities, and identified a far wider range of activity goals than in studies.[79] People with chronic pain involved in codesign of sensing technology and related apps can make outputs meaningful for their self-management; in other medical conditions, users have even hacked sensors to fit their needs.[69] Better understanding of social demands, barriers, and opportunities for sensing technology needs user involvement.[25] Few studies in this review addressed social interaction; the 3 exceptions[74,95,96] explored novel aspects of the impact of chronic pain on social activity, providing a basis for further studies.

5. Conclusion

These lessons, and some uses of sensors in the mental health field, offer potential tools to the study of pain. Considering the

profound influence of psychological and social factors in chronic pain, future studies may focus on leveraging current technology to gain a more comprehensive understanding of chronic pain in context. Understanding context is essential for meaningful interpretation of sensor data and can be supported (for instance) by explicit definitions of metadata. It is crucial, however, that public participants are involved in discussing assumptions about what context is relevant. Ground truth is often unspecified, yet it is pivotal to guide the interpretation of sensor data in relation to target behavior or characteristic that is being sensed. Finally, current advances in machine learning and artificial intelligence, portable sensing technology, and computing power open the possibility for future studies to analyse multidimensional and high-dimensional sensor data to explore some of the complexities of the chronic pain experience.

Conflict of interest statement

The authors have no conflicts of interest to declare.

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