Just-in-time adaptive interventions for behavior change in physiological health outcomes and the use case for knee osteoarthritis: a systematic review

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Abstract

Background: Prevalence for knee osteoarthritis (KOA) is high and patients profit from individualized therapy approaches. Here, just-in-time adaptive interventions (JITAIs) are upcoming digital interventions for behavior change.

Objective: This systematic summarizes the features and effectiveness of existing JITAIs regarding important parameters for KOA management and derives the most promising features to the use case of KOA.

Methods: The electronic databases PubMed, Web of Science, Scopus, and EBSCO were searched using keywords related to JITAIs, physical activity, sedentary behavior, physical function, quality of life, pain, and stiffness. JITAIs for adults that focused on the effectiveness of at least one of the selected outcomes were included and synthesized qualitatively. Study quality was assessed with the Quality Assessment Tool Effective Public Health Practice Project (EPHPP).

Results: A total of 31 studies with mainly weak overall quality were included in this review. The studies were mostly focused on physical activity and sedentary behavior and no study examined stiffness. The design of JITAIs varied with a frequency of decision points from a minute to a day, device-based measured and self-reported tailoring variables, intervention options including audible or vibration prompts and tailored feedback, and decision rules from simple if-then conditions based on one variable to more complex algorithms including contextual variables.

Conclusions: The use of frequent decision points, device-based measured tailoring variables accompanied by user input, intervention options tailored to user-preferences, and simple decision rules showed the most promising results in previous studies. This can be set up using target variables for a KOA JITAI that include breaks in sedentary behavior, and an optimum of physical activity considering individual knee load for health benefits of patients. Clinical Trial: https://osf.io/y2hcd/

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Abstract

Background:

Prevalence of knee osteoarthritis (KOA) is high and patients profit from individualized therapy approaches Just-in-time adaptive interventions (JITAIs) are upcoming digital interventions for behavior change.

Objective:

This systematic review summarizes the features and effectiveness of existing JITAIs regarding important physiological health outcomes and derives the most promising features to the use case of KOA.

Methods:

The electronic databases PubMed, Web of Science, Scopus, and EBSCO were searched using keywords related to JITAIs, physical activity, sedentary behavior, physical function, quality of life, pain, and stiffness. JITAIs for adults that focused on the effectiveness for at least one of the selected outcomes were included and synthesized qualitatively. Study quality was assessed with the Quality Assessment Tool Effective Public Health Practice Project (EPHPP).

Results:

A total of 45 studies with mainly weak overall quality were included in this review. The studies were mostly focused on physical activity and sedentary behavior and no study examined stiffness. The design of JITAIs varied with a frequency of decision points from a minute to a day, device-based measured and self-reported tailoring variables, intervention options including audible or vibration prompts and tailored feedback, and decision rules from simple if-then conditions based on one variable to more complex algorithms including contextual variables.

Conclusion:

The use of frequent decision points, device-based measured tailoring variables accompanied by user input, intervention options tailored to user-preferences, and simple decision rules showed the most promising results in previous studies. This can be transferred to a JITAI for the use case of KOA by using target variables that include breaks in sedentary behavior, and an optimum of physical activity considering individual knee load for health benefits of patients.

Keywords: eHealth, physical activity, sedentary behavior, pain, physical function, quality of life

1 Background

Osteoarthritis (OA) is one of the most common chronic joint conditions, which leads to pain, stiffness, and reduced physical function, which in turn diminishes quality of life (QoL) [1,2]. The most commonly affected weight-bearing joints are the knees, followed by the hips [3]. In 2019, about 344 million people worldwide were living with an OA severity level that could benefit from effective therapy and this number will grow over the next years [4]. Appropriate mechanical stimuli, including physical activity (PA), are joint health protecting factors [5]. Furthermore, an adequate level of PA and reduced sedentary behavior (SB) results in reduced pain and improves physical function and stiffness in knee osteoarthritis (KOA) patients [6–10]. Thereby, the QoL of people that are affected can also be improved [11]. Treating pain and overcoming functional limitations are essential for preventing a downward spiral of reduced PA and declining QoL [12]. Inadequate PA can lead to excess bodyweight, which increases mechanical joint loading for example during locomotion and accelerates the degenerative process of KOA [13]. Furthermore, individuals with KOA are more prone to cardiovascular disease (CVD), as factors, such as reduced PA, are also correlated with elevated CVD risk [14]. Consequently, PA and exercise is recommended for preventing such disease [14]. Additionally, PA and exercise have shown to be beneficial in terms of alleviating KOA symptoms such as pain and stiffness [15]. Previous research has highlighted the importance of new strategies to encourage KOA patients to participate in greater levels of PA [13,16]. However, KOA is a highly heterogeneous and multifactorial disease which affects individuals differently with variations in disease progression, severity, and response to treatments [13]. As a consequence, an individualized therapy approach is suggested to effectively manage the symptoms and slow down the progression of the disease and promoting a healthy lifestyle specifically tailored to each person [17]. While this is also possible for interventions that are delivered in person, mobile health (mHealth) interventions are upcoming methods with the opportunity to deliver such highly individualized interventions at a larger scale. mHealth interventions are defined as medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants, and other wireless devices [18]. These interventions profit from the fast development of accompanying sensors like accelerometers and heart rate monitors [19] which allow for ecologically valid real time interventions. Previous studies show promising results for PA promotion and the reduction of SB if a theoretical foundation and behavior change techniques were used for the intervention [20]. In the context of KOA, reviews point to a good usability and the potential for effective interventions but the research is in an early stage [21,22]. A review including mHealth interventions for KOA points out, that most available apps lack scientific studies backing their effectiveness but those evaluated by RCTs show promising results concerning pain, physical function, and PA [23]. The main features of these apps included exercise prescription and the tracking of symptoms. A special case of mHealth interventions of which patients with KOA could benefit greatly are the highly individualized just-in-time adaptive interventions (JITAIs) or ecological momentary interventions (from here on only the term JITAI is used). These aim to generate real-time or near real-time feedback by leveraging prior knowledge of individuals and previously collected data. With this compiled, dynamic knowledge, tailored interventions and nudges can be delivered when needed via mobile technologies, aligned with the individual's context and requirements [24]. These nudges can then change proximal outcomes like step count in order to achieve the ultimate distal goals of the JITAI like better joint health and QoL [25]. An intervention is defined as a JITAI if it corresponds to real-time needs, adapts to input data, and is triggered by the system with the aim to deliver the intervention at a state of both vulnerability/opportunity and receptivity of participants [25–28]. In the context of designing JITAIs, decision points represent the specific points in time when the JITAI can be triggered, while decision rules are the criteria that are applied at a decision point to determine if the JITAI should be triggered and which intervention option should be used. Intervention options refer to the possible actions that the JITAI can take at a decision point, while tailoring variables denote the sensor or user-input that is used for adaptation [26]. A previous review on JITAIs for PA promotion by Hardeman and colleagues [28] and a meta-analysis for device-based measured health outcomes by Xu and colleagues [29] point to the feasibility and preliminary effectivity of JITAIs to promote PA and reduce SB. However, further variables (i.e. physical function, stiffness, pain, and QoL) are important to KOA [8–11] that were not considered in previous works. Additionally, previous reviews did not aim to clearly depict decision points, tailoring variables, intervention options, and decision rules from the literature. This, however, is important to build a foundation for future JITAI designs. Lastly, JITAIs are an upcoming field with new studies getting published frequently warranting frequent updates of the literature.

This review aimed to systematically summarize the literature regarding the features of JITAIs of important physiological health outcomes and proxies (i.e. PA, SB, physical function, QoL, pain, and stiffness). The second aim was to extract the most promising features which should be considered by future JITAIs in the treatment of KOA.

2 Methods

2.1 Design

This systematic review was registered on the Open Science Framework [30] on 07 March 2022. It was carried out based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) expanded checklist [31].

2.2 Inclusion criteria

Inclusion and exclusion criteria were formulated according to PICOS.

1. **P**articipants in the studies must be over 18 years, regardless of sex and gender. Thus, the only exclusion criterion relates to studies which only included participants under 18 years of age. Studies were included if <50% of participants were >18 years.
2. **I**ntervention: All studies which use a digital physiological treatment that can be defined as a JITAI are included in this review. If studies use other types of interventions in addition to JITAIs, they are still included and only the JITAI parts were considered. Furthermore, there were no restrictions regarding the duration of the intervention, the number of intervention sessions or the technical device for the intervention.
3. **C**omparator: There was no restriction regarding control. We included active control (e.g., other physiological treatments or interventions), passive control (no intervention/treatment), and studies with no control group.
4. **O**utcome: Studies were included whenever they evaluated the effectiveness of a JITAI regarding one of the parameters PA, SB, pain, QoL, physical function, and/or stiffness as a main outcome. This also included all parameters that are synonyms or components to the previously mentioned parameters.
5. **S**tudy design: We included all study types, except reviews or meta-analysis. The only important thing was that the study reported on the effectiveness of the intervention.

2.3 Search strategy

The electronic databases PubMed, Web of Science, Scopus, and EBSCO were used to identify relevant studies. Since search strategies exclusively relying on databases have shown to be non-exhaustive [32], the reference list of all selected articles was checked for further relevant studies. Initial searches were conducted on October 26th, 2022 and the search was rerun on April 9th, 2024. We combined different search terms related to the intervention type, the area of mobile health, and the outcome parameters. Further details are available in the Additional file 1.

2.4 Paper selection

All identified studies were exported to a reference management tool (EndNote or Citavi). The reference management tools were used to remove all duplicates. Then, all titles were checked for eligibility by MB and JF independently. Second, the abstracts were screened and, third, the full texts of all remaining papers were screened and the reasons for exclusion were noted by the two authors. Any disagreements at one of the screening steps were resolved by discussion until consensus was found.

2.5 Study quality assessment

The Quality Assessment Tool Effective Public Health Practice Project (EPHPP) was used for the evaluation of the study quality. It is specifically designed tool to test and support findings in public health research and refers to articles related to a broad number of health-related topics, including chronic diseases [33]. By evaluating six different criterions, a global rating was assessed at the end for each study (see Table 4). Every criterion could be rated “weak” (red), “moderate” (yellow) or “strong” (green) which finally influences the global rating. One “weak”-rating leads to a “moderate” global rating and two or more “weak”-ratings result in a “weak” global rating. Only studies without a “weak”-rating can achieve a “strong” global rating [33].

2.6 Data extraction

All important information of the selected studies has been reproduced in tabular form in the section “Results”. The preparation of the tables and their contents were developed by MB and JF in consultation with BS. For the most accurate rendering of the study content, reference was made to the study characteristics including study design, sample size, population and setting as well as characteristics of the participants. To provide starting points for future JITAIs, the features and delivery of the JITAIs including decision points, tailoring variables, intervention options, and decision rules based on the JITAI framework [27] and the duration of the interventions were also extracted from the existing studies. To display effectiveness and theoretical foundation, all data regarding retention, measurement and the significant within- or between group differences of the intervention and the use of behavior change techniques (BCTs) stratified by control and intervention group according to Michie et al. [34], and the theoretical foundation of the interventions are displayed in the results section.

3 Results

3.1 Study selection

A total of 4340 papers were exported to Endnote/Citavi and screened (see Fig. 1). Initially, 571 duplicates were excluded by the reference management tools and another 279 duplicates were removed manually. The remaining 3490 papers were screened for their titles and 3133 were excluded by the authors. Thus, 357 abstracts were read, and 213 more papers were excluded at this step. The updated search yielded 1215 additional papers including 145 duplicates. The 1070 unique paper were screened for title and abstract, and the remaining 88 papers for full texts. The main reasons for exclusion were that it was no intervention study, the intervention did not qualify as a JITAI, the outcome did not fit the inclusion criteria, it was a systematic review or meta-analysis, or all participants were younger than 18 years old. Full texts of the remaining 144 studies were screened and finally 18 papers were included into the review supplemented by additional 14 paper from the updated search. During the screening process, 13 more studies were added. Nine studies were adopted from the systematic review by Hardeman et al. [28], and four additional papers were found during data extraction by checking references of the included studies. Finally, 45 studies are presented and summarized in Tables 1-3.

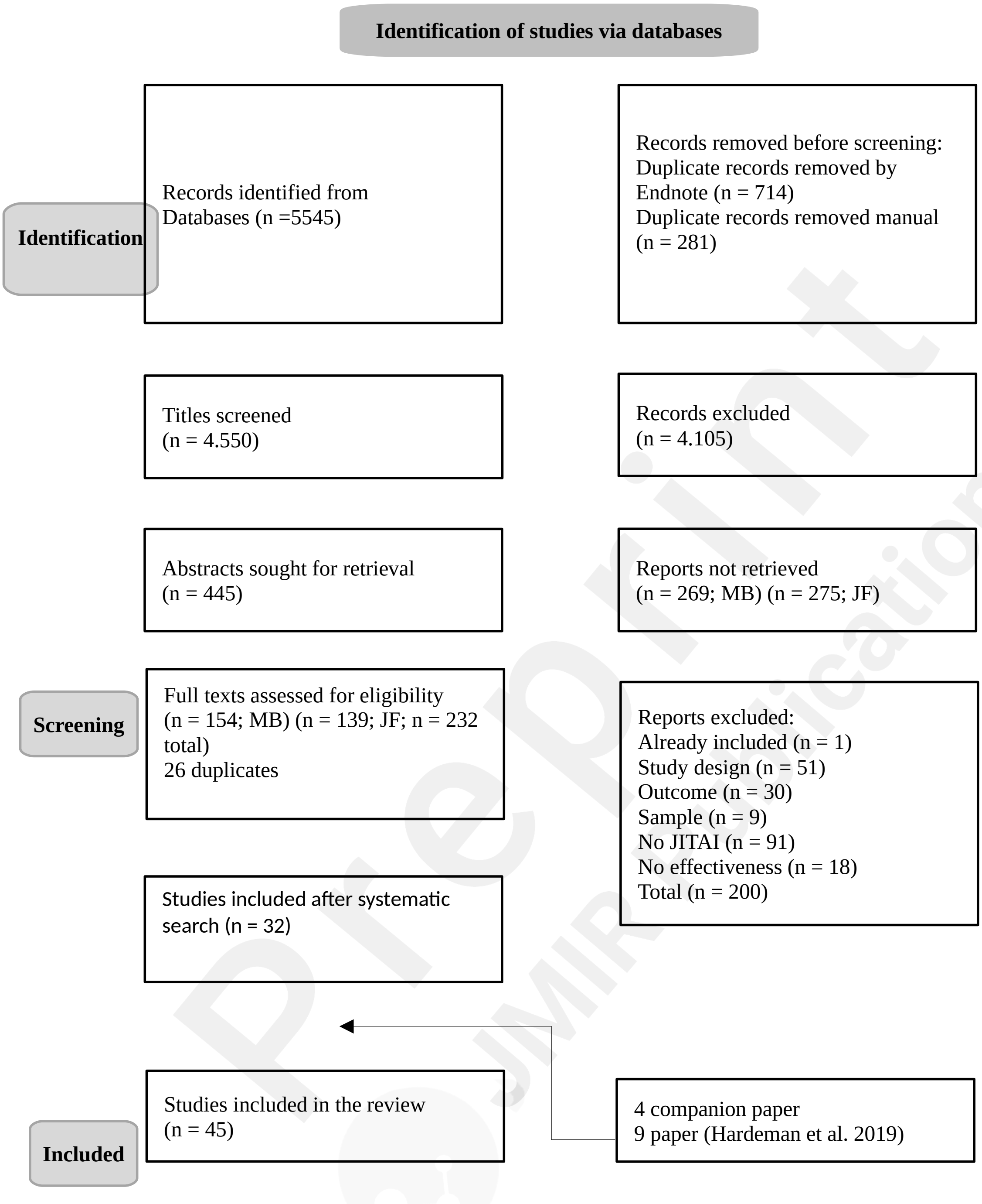

Fig. 1 PRISMA flow diagram

3.2 Description of the included studies

Twenty-five studies were conducted in the US, 9 in the Netherlands, 2 in Australia, 2 in Germany and the others in New Zealand, China, Qatar, Finland, Israel, Spain and Belgium. Most of them (26/45, 58%) were designed as feasibility study/pilot evaluations and they were mainly randomized controlled trials (23/45, 51%). Nine out of 45 were conducted in a single-group pre-post design, 3 as a secondary analysis using a within-person design for the intervention group, 2 as a controlled within-person trial, 2 as a mixed-method evaluation and all other studies were either a retrospective cohort study, a randomized within-person study or combined different study designs. The minimum number of participants was eight (three studies) and the maximum was 981 participants with an average of 99 (SD = 175) participants. Two studies focused exclusively on women and overall 62% (2434/3960) of all participants were women and 38% (1516/3950) were men. The mean age in 19 studies was > 50 years and they focused mainly on a specific population like sedentary people, patients with chronic diseases (e.g. chronic obstructive pulmonary disease (COPD), coronary heart disease), or cancer survivors. Retention in 3 studies was less than 50%, 4 studies were below 80%, 21 were equal to or above 80 and below 100% and the remaining 12 studies had a full retention. PA was the most common outcome (39 studies) followed by 19 studies that used parameters of SB as an outcome, of which 18 studies considered both PA and SB. Nine studies examined the impact on quality of life, 4 used synonyms of physical function, and 3 studies used pain as an outcome. None of the included articles referred to stiffness. Detailed results are displayed in Table 3. An average of 8 BCTs (SD = 7) were included for the intervention group and 4 (SD = 5) for the control group. The number of BCTs in the intervention group ranged from two to 47, compared with one to 27 in the control group. The intervention duration ranged from 1 day to a max of 12 months Klicken oder tippen Sie hier, um Text einzugeben. with a typical duration of 3-6 weeks. One study had no time restriction but a step count of 166.000 as cut off for the intervention duration [35]. Details on BCTs and theoretical foundation can be found in the Additional file 2.

Table 1: Study characteristics; (IG = intervention group, CG = control group, M=mean, SD = standard deviation, PA = physical activity, SB =sedentary behavior, COPD = chronic obstructive pulmonary disease)

Author, year, and country of study	Study design	Population and activity profile	Analyzed sample size	Participant characteristics (age, gender, ethnicity)
Allicock et al. [36], **US**	Feasibility study/pilot evaluation. Randomized Controlled Trial.	Female African American Breast Cancer Survivors. Healthy enough to engage in moderate to vigorous-intensity PA.	N = 22 (IG = 13; CG = 9)	Age: M(SD) = 52.2 (9.2) years 0% male. 100% African American.
Baumann et al. [37], **Germany**	Multi-arm parallel-group randomized controlled trial.	Healthcare professionals (nursing staff and office workers) aged 18 years and older.	N = 170. (IG 1 = 21, IG 2 = 23, IG 3 = 7, IG 4 = 34, IG 5 = 16, CG = 69)	Age: M(SD) = 41.1 (10.9) years. 39% male.
Bond et al. [38]; **Thomas & Bond** [39] **US**	Feasibility study/pilot evaluation. Randomized within-person study. The participants were randomized each week to one of the three different conditions.	Overweight/Obese Adults. No exclusion based on PA level.	N = 30	Age: M(SD) = 47.5 (13.5) years. 17% male. 67% White, 13% African-American, 3% American Indian/ Alaskan Native, 3% Asian, 13% Other.
Bort-Roig et al. [40], **Spain**	Randomized Controlled Trial.	Desk-based employees at-work and away from work. Low activity level outside work. No physical or health problems that limited their ability to stand for bouts of at least 10 mins.	N = 141. (IG = 90; CG = 51) Follow-up: N = 64 (IG = 42; CG = 22)	Age: M(SD) = 45 (9) years. 18% male.
Brakenridge et al. [41,42], **Australia**	Cluster-randomized workplace trial. Mixed-methods evaluation.	Desk-based office employees. Not reported.	N = 153 (IG = 66; CG = 87) Only IG data was used for 2018 results.	IG: Age: M(SD) = 37.6 (7.8) years. 47% male. CG: Age: M (SD) = 40 (8) years. 60% male.
Carlozzi et al. [43], **US** **Wang et al.** [44], **US**	**Carlozzi et al.** Feasibility study/pilot evaluation. Randomized Controlled Trial. **Wang et al.** Pilot evaluation. 2-arm microrandomized	Care partners who are 18 years old and are caring for an individual 18 years or older.	**Carlozzi et al.** N = 70 (IG = 36; CG = 34) **Wang et al.** N = 36 (IG of Carlozzi et al.)	IG: Age: M(SD) = 54.4 (13.1) years. 22% male. 81% Caucasian, 3% African American, 8% Asian. CG: Age: M(SD) =56.1 (14.5) years.

	controlled trial			35% male. 97% Caucasian, 3% African American.
Compernolle et al. [45]**, Belgium**	Single group pre-post design.	Age > 60 years. Able to walk 100 meters without difficulties.	N = 26	Age: M(SD) = 64.4 (3.8) years. 50% male. 100% flemish.
Conroy et al. [46]**, US**	Pilot evaluation. Secondary data analysis using a within-person design.	Insufficiently-active young adults aged between 18 and 29 years.	N = 58	Age: M(SD) = 24.6 (3.1) years. 31% male. 69% White, 31% Other.
Ding et al. [47]**, US**	Feasibility study/pilot evaluation. Randomized controlled trial.	College students. Participants who were in the contemplation and preparation stage based on the Transtheoretical model.	N = 16 (IG = 9; CG = 7)	Age: 18 – 25 years. 63% male. Other characteristics not reported.
Direito et al. [48]**, New Zealand**	Feasibility study/pilot evaluation. Single-group pre-post design.	Adults who didn´t meet PA recommendations or who did meet recommendations but intended to decrease sedentary time.	N = 69	Age: M(SD) = 34.5 (11.8) years. 22 % male. 54% New Zealand European, 46% Other.
Fiedler et al. [49]**, Germany**	Cluster-randomized controlled trial. Secondary data analysis using a within-person design for the intervention group.	Families (at least 1 parent and 1 child). Not reported.	N = 80	59% adults. 53% male
Finkelstein et al. [50]**, US**	Feasibility study/pilot evaluation. Randomized controlled crossover study.	Sedentary, overweight women. Daily inactivity > 3 hours.	N = 30	Age: M(SD) = 52 (12) years. 0% male. 47% White, 47% African American.
Freene et al. [51]**, Australia**	Feasibility study/pilot evaluation. Single-group pre-post design.	Adults with a stable coronary heart disease. Able to perform a submaximal walking test.	N = 20	Age: M(SD) = 54 (13) years. 85% male. 61% Australian.
Fundoiano-Hershcovitz et al. [52]**, Israel**	Retrospective cohort study.	Adults with high pain levels and more than six weekly training hours (users with less than six weekly training hours were used for the sensitivity analysis).	N = 981	Age: M(SD) = 39.2 (29) years. 39% male.
Garland et al. [53]**, US**	Feasibility study/pilot evaluation. Randomized controlled trial.	Adult opioid-treated chronic pain patients.	N = 63	Age: M(SD) = 53.6 (12.8) years. 59% male. 92% white, 8% other.
Golbus et al. [54]**, US**	Randomized Clinical Trial.	Low to moderate risk 18–74 years old patients in cardiac rehabilitation.	N = 223 (IG = 112; CG = 111)	Age: M(SD) = 59.6 (10.6) years. 69% male.

				84% White, 16% Others.
Hermens et al. [55]; **Tabak et al.** [56], **The Netherlands**	Feasibility study/pilot evaluation. Quasi-experimental study: Single-group pre-post design.	People living with COPD who had completed a lung rehabilitation program three months before the study.	N = 8	Age: 49–64 years. 60% male.
Hietbrink et al. [57], **The Netherlands**	Mixed methods longitudinal study.	Adults with Type 2 Diabetes	N = 20 N = 15 (Physical activity module) N = 5 (Nutritional module)	Age: M(SD) = 68.0 (8.0) years. 70% male.
Hiremath et al. [58], **US**	Non-randomized pilot evaluation. Single-group pre-post design.	Individuals with spinal cord injury (SCI) Use a manual wheelchair and self-propel them. No active pelvic or thigh wounds, cardiovascular disease, or pregnancy.	N = 20	Age: M(SD) = 39.4 (12.8) years. 80% male. 12.4 (12.5) years since injury.
Ismail & Al Thani [59], **Qatar**	Experimental study (between-group design). Controlled trial.	Adults with a predominantly sedentary job. Able to walk.	N = 58 (IG = 29; CG = 29).	Age: 23-39 years 34% male (IG), 41% male (CG).
Klasnja et al. [60], **US**	Feasibility study/pilot evaluation. Single-group pre-post design. 2x2 factorial experiment. Within-person microrandomized trial.	Obese adults after bariatric surgery.	N = 45	Age: M(SD) = 45 (11.9) years. 16% male. 80% White, 7% Black, 2% Other, 7% Mixed.
Li et al. [61], **US**	Feasibility study/pilot evaluation. Single-group pre-post design.	No prior diagnosis of cognitive impairment or dementia, sedentary lifestyle (self-reported more than 6 h of sitting activities per day), poor sleep quality (Insomnia severity index ≥ 8), and no diagnosis of sleep apnea.	N = 8	Age: M(SD) = 74 (5.42) years. 25% male. 50% White, 50% Black.
Low et al.[62], **US**	Usability and Feasibility Study. Single-group pre-post design.	Adults with abdominal cancer post-surgery. Able to stand and walk unassisted.	N = 15	Age: M= 49.7 years. 20% male. 87% White, 13% Black.
Low et al. [63], **US**	Feasibility study/pilot evaluation. Randomized Controlled Trial.	Adults scheduled for surgical treatment of metastatic gastrointestinal or peritoneal cancer and able to stand and walk unassisted.	N = 26 (IG = 13, CG = 13)	Age: M(SD) = 56.2 (10.5) years. 58% male. 92% White, 4% Black, 4% more than one.
Martin et al. [64], **US**	Randomized Clinical Trial.	Outpatients of an academic cardiac vascular disease prevention center. Self-reported moderate or vigorous leisure-time ≥ 30min/day at <3 days/week.	N = 48 (Unblind, no texts = 16; Unblind, texts = 16; Blind = 16).	Age: M(SD) = 58 (8) years. 54% male. 79% White.

McEntee et al. [65]**, US**	Randomized trial.	Inactive, healthy adults	N = 512 (n = 128 per study group)	Age: M(SD) = 45.5 (9.1) years. 36% male. 19% Hispanic, 6% African American, 2% Asian, 84% White.
Nurmi et al. [66]**, Finland**	Pilot evaluation. N-of-1 Randomized Controlled Trial.	General population >18 years. No contraindications to engaging in physical activity, no use of any PA trackers or PA apps in the previous 6 months, no participation in other trials or behavior change programs in the previous 6 months or during the trial, below 150 MVPA/week	N = 15	Age: M(SD) = 42.3 (9.8) years. 27% male.
Pellegrini et al. [67]**, US**	Feasibility study/pilot evaluation. Quasi-experimental study. Single-group pre-post design.	People living with type 2 diabetes. Sedentary occupation or spend ≥ 75 % of the day sitting.	N = 9	Age: M(SD) = 53.1 (10.7) years. 23% male. 23% White, 77% Black.
Rabbi et al. [68]**, US**	Feasibility study/pilot evaluation, within-subject. Randomized Controlled Trial.	Volunteers, including students and professionals. Not reported.	N = 17	Age: M(SD) = 28.3 (6.96), 18–49 years. 53% male.
Rabbi et al. [69]**, US**	Feasibility study/pilot evaluation. Quasi-experimental study: Controlled within-person trial.	Employees of Cornell University. Not reported.	N = 16	Age: 18–29 years: 25.0%. 30–39 years: 38%. 40–49 years: 19%. > 50 years: 19%. 44% male.
Rabbi et al. [70]**, US**	Feasibility study/pilot evaluation. Single-blinded, controlled within-person trial.	Adults with chronic back pain (>6 months in duration). Able to walk without mobility aids.	N = 10	Age: 31 – 60 years. 30% male.
Radhakrishnan et al. [71]**, US**	Feasibility study/pilot evaluation. Randomized Controlled Trial.	Adults with heart failure. Able to walk.	N = 38 (IG = 19; CG = 19)	Age: 55 years or older. 53% male 76% White, 16% African American, 3% Native American, 5% Other
Robertson et al. [35]**, US**	Feasibilty study/pilot evaluation. Randomized Controlled Trial.	Adult cancer survivors. Didn´t meet the recommended activity levels.	N = 78 (IG = 39; CG = 39)	Age: 18-34 years: 5%, 35-49 years: 26%, 50-64 years: 33%, 65-74 years: 33%, >74 years: 3%.

				9% male. 1% American Indian or Alaska native, 17% Black or African American, 79% White, 1% Other.
Sporrel et al. [72], **The Netherlands**	Feasibility study/pilot evaluation. Randomized controlled trial design with single-group pre-post evaluation.	Adults between 18 and 55. Didn´t meet WHO PA guidelines and no medical condition that made it unsafe to engage in unsupervised PA.	N = 20 (Smart PAUL = 11; Basic PAUL = 9)	Age: M(SD) = 30.65 (8.4) years. 15% male.
Stuber et al. [73]**, The Netherlands**	Parallel cluster-randomized controlled trial	30–80 year old adults, regular shoppers at a participating supermarket (self-reported to purchase > 50% weekly groceries at a participating supermarket)	N = 361 (IG = 162; CG = 199)	IG: Age: M (SD) = 58.9 (11.5) years. 29% male. CG: Age: M (SD) = 57.2 (10.2) years. 26% male.
Tabak et al. [74,75]**, The Netherlands**	Randomized controlled pilot trial. Secondary data analysis using a within-person design for the intervention group.	Patients with COPD. a clinical diagnosis of COPD, no infection or exacerbation in the 4 weeks prior to start of the study, and a current or former smoker.	N = 30 (IG = 14; CG = 16)	IG: Age: M (SD) = 65.2 (9) years. 57% male. CG: Age: M (SD) = 67.9 (5.7) years. 69% male.
Valle et al. [76,77]**, US**	Randomized controlled trial	18-39 year old patients with a cancer diagnosis in the previous 10 years. engaging in <150 minutes/week of MVPA	N = 280 (IG = 140; CG = 140)	Age: M(SD) = 33.4 (4.8) years. 18% male. 23% racial/ethnic minorities
Van Dantzig et al. [78]**, The Netherlands**	Feasibility study/pilot evaluation. **Study 1:** Qualitative study. **Study 2:** Randomized controlled trial.	**Study 1:** Office workers. **Study 2:** Healthy office workers. **Study 1:** Not reported. **Study 2:** Sedentary job, no known physical handicap or other condition that makes physical activity (walking) impossible, older than 30 years, not participating in another physical activity intervention.	**Study 1**: N = 8 **Study 2:** N = 86 (IG = 40; CG = 46)	**Study 1:** Age: Not reported. 50% male. **Study 2**: Intervention group: Age: M(SD) = 44.5 (7.9); 30–57 years. 58% male. Control group: Age: M(SD) = 44.3 (8.0); 32–63 years.

				63% male.
Van Dantzig et al. [79]**, The Netherlands**	Substantive evaluation. Randomized controlled trial.	Desk workers with regular (daytime) working hours. Not reported.	N = 70 IG/CG Not reported	Age: 18–65 years. 73% male (based on N = 70 recruited).

3.3 Key features of JITAIs

Detailed key features of the includes JITAIs are displayed in Table 2.

Most decision points at which a JITAI could potentially be triggered were set to short time intervals which were either specified to one decision point each minute (n=11) or not clearly specified but indicating short time intervals (n=21). Further, 5 studies set decision points to time frames of 10 minutes up to two hours, and 11 were set to multiple times per day up to daily.

Tailoring variables used for JITAI adaptation were mainly device-based measured by accelerometer, smartphone, or smartwatch and concerned PA and SB outcomes supplemented with variables like time, weather, or location. Ten studies used self-reported tailoring variables through a Baseline questionnaire [64], through EMA [36,43,44,57], or via non specified methods to assess pain and fatigue [62,63], to enable non-specified user-input [53], or to supplement PA data if the device has not been worn [68–70].

Intervention options at decision points included mainly the delivery of an audible or vibration prompt to participants accompanied by tailored feedback, information about health behavior, and/or suggestions for behavioral alternatives. One study explicitly explained in the prompt why the prompt occurred [47]. The alternatives based on the decision rules were mainly not to send the prompt for the decision points with short time frames while those with longer timeframes had different intervention options depending on the tailoring variables.

Decision rules defining opportune moments were mainly based on if-then conditions. This means that an opportune moment was defined if a certain threshold – e.g. 20 minutes of SB [67], less than 100 steps in one hour [49], a bout (≥3min) of MVPA (or higher) PA was performed [58], lumbar posture [41,42], time, location, or weather-based thresholds [78]– was met. Most decision rules were based on one if-then condition while some used if-then decision trees. More complex models applied multi-armed bandit algorithms (sequential decision-making algorithm [80]) [68–70], pareto-frontier algorithm (taking user-preferences into account [81]) [69], pre-learned reinforcement learning models (models that make use of historical data and of data during the trial[82]) [72], k-nearest neighbor classifier (one of the most fundamental and simple classification methods [83]) , and real-time prediction and self-learning by a support vector machine (a classical machine learning technique [84]) [55,56]. If the conditions for an opportune moment were met, intervention options were delivered which included both fixed responses and micro randomized suggestions (e.g. [60]) for behavior change.

Table 2: Key facets and duration of the JITAI (IG = intervention group, CG = control group, PA = physical activity, SB =sedentary behavior, EMA = ecological momentary assessment, MET = metabolic equivalent of task, MVPA = moderate to vigorous physical activity)

Author (year)	**Decision points** Time when intervention decision is made	**Tailoring variables** Assessment determining intervention delivery (only the JITAI relevant ones)	**Intervention Options** Possible actions to be performed at decision points	**Decision rules** Link between intervention options and tailoring variables at decision points	**Duration of intervention**
Allicock et al. [36]	EMAs: (3 types) 1) Daily diary assessments: Each morning (i.e. 30 min after typical wake up). 2) Random sampling assessments: Twice per day. 3) Event sampling assessments: Before and after exercise and meals.	Answers to EMA (related to PA, not specified). Self-report. Not further specified.	Tailored feedback to EMAs. Not further specified.	Opportune moment: after participants filled out an EMA → they received tailored feedback. Not further specified.	4 weeks.
Baumann et al. [37]	Not clearly specified, short time intervals (e.g. minute).	Heart rate and physical activity device-based measured by ECG sensors and accelerometry	Prompt to interrupt inactivity with randomly selected pre-defined motivational messages was sent.	Opportune moment: during wake time (operationalized based on the heart rate measurement) if 30 minutes of inactivity were detected by the accelerometer. → prompt was sent	8 weeks.
Bond et al. [38]; **Thomas & Bond** [39]	Each minute.	SB (≤1.5 METs). Device-based measured real-time data by smartphone accelerometry.	Audible prompt to take a physically active break from sedentary behavior was sent. Participants could respond to the prompt by performing a physical activity break, silencing the prompt, or delaying the prompt by 30 minutes. Reminders to meet the prompt.	Opportune moments: 1) 30 continuous sedentary minutes (3min walking break). 2) 60 continuous sedentary minutes (6min walking break). 3) 120 continuous sedentary minutes (12min walking break). was met → a respective walking break	3 weeks (1 week each condition in counterbalanced order).

				prompt was sent. If participants performed a physically active break, they received positive feedback plus a green "go" light on the dashboard. When not silenced/delayed, an additional prompt was sent after 5- and 10-min continued SB	
Bort-Roig et al. [40]	Each minute.	SB (sitting time). Device-based measured real-time data by W@W-App and smartphone inbuilt accelerometer.	Vibration prompt to take a break from sedentary behavior	Opportune moment: participants sat for more than 60 minutes a vibration prompt was sent through the mobile phone.	13 weeks in total. 8 weeks ramping phase & 4 weeks maintenance phase.
Brakenridge et al. [41,42]	Not clearly specified, short time intervals (e.g. minute).	SB (sitting time), and Posture (pelvic tilt angle). Device-based measured real-time data by LUMOback activity tracker + mobile app.	Push notification (vibration of sensor).	Opportune moment: when in a poor lumbar posture + after user-defined time sitting (15min, 30min, 40min, 1h or 2h) → a vibration was sent if they were in a poor lumbar posture + push notification after sitting. If they selected a time interval for the push notification, then a push notification was sent to the app after the user-defined time interval.	3 months. With possibility to expand to 12 months.
Carlozzi et al. [43] **Wang et al.** [44]	Each minute within a participant chosen 5-hour window.	Step count, sleep quality and HRQOL. Device-based measured real-time data by accelerometer (Fitbit) and self-reported in the mobile app (CareQOL).	Daily personalized push notification. Notification content was randomly drawn from a pool of over 400 messages of the following types: 1) Data feedback, 2) Facts, 3) Tips, 4) Support.	Opportune moment: 50/50 chance of receiving notifications each day. Based on accelerometry data and after daily real-time rating (3 questions) of HRQOL	**Carlozzi et al.** 2 hour baseline virtual study visit. 10 day run-in period. 90 day intervention

			Messages were personalized based on step count and HRQOL data.	--> Push notification was sent. Notifications are triggered in a personalized 5 hour timeframe	**Wang et al**. 3 months.
Compernolle et al. [45]	Each minute.	SB (sitting time). Device-based measured real-time data by accelerometer (Activator).	Vibration of the accelerometer. Participants were instructed to break up their SB each time they received the vibration.	Opportune moment: after 30 uninterrupted minutes of sitting time → Vibration prompt was sent	3 weeks.
Conroy et al. [46]	Not clearly specified, short time intervals (e.g. minute) within a participant chosen 10-hour window.	PA (stepping time) Device-based measured real-time data by wrist worn accelerometer.	Prompts were either aiming on self-monitoring or behavioral feedback. Self-monitoring: Participants had to report the number of minutes being active in the past 2 hours. Behavioral feedback: Participants get shown the number of minutes being active in the past 2 hours.	Opportune moment: 0-6 prompts per day were randomly sent within a self-selected messaging window and were based on activity duration of last 2 hours. The number, type, and timing of prompts each day were determined randomly by the server without any involvement by the researcher.	90 days.
Ding et al. [47]	Not clearly specified, short time intervals (e.g. minute).	Smartphone usage (app-usage api), PA (activity recognition api), SB (SB recognition api), and meals (smart watch). Device-based measured real-time data by smartphone, Pebble smartwatch Android.	Motivational prompt to walk and prompt to walk more (when already walking). With an explanation of why the prompt occurred.	Opportune moment: 1) Participants overused their smartphone 2) Participants had been sedentary for a long time 3) Participants were walking 4) Participants just had their meals → Motivational messages tailored to the respective condition Examples: SB "You sit too long. Walk for	3 weeks.

				a while" Smartphone usage "Less Apps. Stand up and Walk"	
Direito et al. [48]	Upon opening the app (daily).	PA and SB clustered to "Couch potato", "Potterer", and "Techno-Active". Device-based measured daily average by Art of Living app.	Behavior change content on the app. Encouraged daily-life activities, running errands, PA at work, leisure time PA, and replacing SB with light PA.	Opportune moment: opening the app for the first time at a specific day → Users were classified into the three activity profiles based on the previous day. Behavior change content was tailored to the respective activity profile.	8 weeks.
Fiedler et al. [49]	Each minute.	PA. Device-based measured real-time data via accelerometer connected to SMART*FAMILY*2.0-app on the study smartphone.	Prompt to break inactivity with a question about the reason for previous inactivity.	Opportune moment: When inactive for 60 minutes (i.e. <100 steps and <2min with >2MET), during participant specific waketime (max. 7 am-10 pm) if 50 of 60 minutes recorded sensor values were present, and if participants have done less than 60 min MVPA on that day → prompt was sent out	3 weeks.
Finkelstein et al. [50]	Every 10-15 minutes.	PA (steps), Fitbit sync data (website). Device-based measured real-time data by Fitbit connected to monitoring website.	Prompt to take a break by tailored text message with information about consequences of prolonged time sitting and suggestions of ways to have an activity break.	Opportune moment: if Fitbit synchronized recently, and if steps <15 in the past hour. No messages were sent during blackout conditions: 1) Self-reported preferences. 2) participant texted S(X) (no messages for the next X hours) 3) participant texted 'okay' which meant no messages were sent during the next	4 weeks.

				hour. → prompt was sent and tailored to the time of day.	
Freene et al. [51]	Daily.	PA (steps + time spent active), social opportunity (number of new places visited and time spent there), and variety (how much the individual's day differs from an average day). Device-based measured real-time data by Vire App (GPS) and Fitbit Flex (activity data).	Individualized, context-specific, and Data-Driven microbehavioral alternatives (Do´s) for changing a habit and learning new behaviors.	Opportune moment: If more than 60% of the total available data was available, and participants showed a low score in PA, social opportunity and variety on 3 consecutive days → an individualized, context specific Data-Driven Do was sent.	6 weeks.
Fundoiano-Hershcovitz et al. [52]	Not clearly specified, short time intervals (e.g. minute).	Slouching posture. User defined sensitivity for posture indication. Device-based measured real-time data by triaxial accelerometer (UpRight by DarioHealth) located on the upper back.	Vibration cycle with two vibrations and a break of 10s until a good body posture is achieved.	Opportune moment: When a slouching posture based on user-selected sensitivity, is detected by the sensor.	8 weeks.
Garland et al. [53]	Not clearly specified, short time intervals (e.g. minute).	Physiological stress. Devic-based measured real-time data by photoplethysmogram and pulse oximeter sensor (mEMA app + Garmin Vivosmart smartwatch)	Mindfulness practice when a physiological stress metric obtained.	Opportune moment: When stress metric exceeded 1 SD of participant´s moving average value → prompt was sent.	90 days.
Golbus et al. [54]	**Activity notification**: 4 time points (morning, lunchtime, midafternoon, evening) **Exercise planning notification**: Each evening	Weather, day of week, time of day, and duration within the study. Mobile study application	Contextually tailored text messages. Either activity notifications or exercise planning notifications. Possible personalization with a participant's preferred name, loss- or gain-framing, and inclusion of an emoji or hyperlink to the study dashboard	Opportune moment: 25% probability of receiving an activity prompt at each decision point. 50% probability of receiving an exercise message each decision point. Activity notifications are tailored based on 4 dimensions of contexts: weather, day of week, time of day, and phase of cardiac rehabilitation.	6 months.

				Exercise planning notifications are tailored based on 2 dimensions of contexts: season and phase of cardiac rehabilitation.	
Hermens et al. [55]**;** **Tabak et al.** [56]	Not clearly specified, short time intervals (e.g. minute).	PA levels (IMA units), previous motivational cues and 'relevant context factors'. Device-based measured real-time data by HTC Desire S (smartphone) and activity sensor (ProMove 3D wireless activity tracker, Inertia Technology B.V.)	Motivational message, prompt to walk. Messages could be encouraging, discouraging or neutral.	Opportune moment: Constant evaluation of the context of the user by machine learning on the app to find suitable situations for delivery of motivational coaching (predicted by analyzing previous cues and learning when a patient was likely to respond well to the message by relating relevant context factors to patient compliance and content). First phase (no previous data), k-nearest neighbor classifier, second phase uses real-time prediction and self-learning by Support Vector Machine implementation (re-trained periodically). → prompts were sent out and messages were tailored to PA level of participants.	3 months. Participants were asked to use the app at least four days per week.
Hietbrink et al. [57]	Twice a day and weekly.	PA (mean daily step count, self-reported activities). Duration of intervention use, type of chronic disease, time of day, type of behavior goal, goal achievement, and the identified barrier toward goal achievement. Device-based measured real-time data by accelerometer (Fitbit Charge 2) and	Tailored motivational messages selected from a pool of 425 messages. Feedback based on goal achievement and reflective questions for goal achievement of the upcoming week.	Opportune moment: Daily motivational message and feedback based on goal achievement. Intervention options were tailored based on if-then rules to the variables of behavior goal, phase of behavior change,	9 weeks.

		self-reported activities (E-Supporter app)	Step goal which gradually became more difficult. Psychological exercises when a goal was not sufficiently reached and motivation, self-efficacy, mood, stress, or planning was the identified barrier for goal achievement	type of chronic disease, time of day, and goal achievement. There were three types of decision rules: (1) rules that triggered the type of motivational message, (2) rules that triggered feedback on goal achievement, and (3) rules that triggered a type of psychological exercise.	
Hiremath et al. [58]	Each minute.	Wheelchair-based PA (MVPA). Device-based measured real-time data by Android-based smartphone, wrist-worn smartwatch, and Bluetooth-based wheel rotation monitor (Pano-Bike). App: Personal Health Informatics and Rehabilitation Engineering (PHIRE)	Congratulatory Messages and near-real-time, personalized feedback through the smartphone (audio and/or vibration) and smartwatch (vibration).	Opportune moment: about (≥3min) of MVPA (or higher) PA was performed → Near-real-time feedback + Congratulatory message + if goal attained congratulation on the goal attainment (then back to [1]) + if goal exceeded feedback about total number of MVPA that day (then back to [1]) + if goal not reached total minutes of MVPA needed for goal attainment displayed (then back to [1]) + if neither of previous conditions are met no additional message is sent (unclear what this includes then back to [1])	3 months. 1st month - baseline. 2nd month – PA feedback. 3th month – PA feedback with JITAI.
Ismail & Al Thani [59]	Each minute.	SB (≤67 steps/40 min), location, weather information, time information. Device-based measured real-time data by smartphone, MotiFit (CG = MotiFit Lite) app + accelerometer, Open Weather Application Programming	CG: Static reminder messages. IG: Context-aware motivational messages. Context aware messages could relate to goal	Opportune moment: If one of the following conditions was - 30 min before lunchbreak - 1 hour before end of the working day	66 days.

		Interface (API).	achievement, weather, nearby restaurants, parks, gyms, and malls (total of 260 unique motivational messages).	- sitting for 40 minutes. → a motivational message was sent IG: the motivational message was tailored to the context using a decision tree (see Multimedia Appendix 3 of the original publication)	
Klasnja et al. [60]	Up to 5 actionable suggestions a day sent at times the participants thought they would have an opportunity for PA.	PA (steps), weather (not specified). Device-based measured real-time data by Fitbit tools (Fitbit Charge 2 wrist-worn activity tracker + Fitbit App).	Actionable suggestions to walk or disrupt SB. 50% walking suggestions, and 50% anti-sedentary suggestions, if prolonged inactive. Library of over 500 text messages.	Opportune moment: at the predefined 5 decision points → suggestions were micro-randomized: - 0.7 no suggestion - 0.15 walking suggestion - 0.15 anti-sedentary and tailored to time of day, day of the week, and current weather	16 weeks.
Li et al. [61]	Not clearly specified, short time intervals (e.g. minute).	SB (< 100 counts/min). Device-based real-time data by Actiwatch 2 Smartwatch (Moto 360) and Android tablet. Apps: Elderfit.	Prompt that encourages participants toward their goals.	Opportune moment: If >90 mins of inactivity were detected during the day → sedentary alert was sent to the smartwatch	6 weeks in total. 1 week pretest. 4 weeks intervention. 1 week posttest.
Low et al.[62]	Not clearly specified, short time intervals (e.g. minute)	PA (steps), severity of 10 symptoms (e.g. pain, fatigue (scale 0-10)). Device-based real-time data by Fitbit Versa smartwatch + Google Pixel 2 Smartphone + Detective Activity to Supporting Health (DASH) app on smartphone + smartwatch.	Activity prompt "Ready for a short walk?". Possible responses on either the watch or the phone: Yes, No, or Snooze.	Opportune moment: Based on severity of symptoms a threshold for SB triggers was set for 2 cases: - All symptoms were rated less than 7 then 60 min SB (less than 50 steps) -Any symptom was rated 7 or higher then 120 min SB → prompt was sent If participants chose Snooze the prompt was repeated 15	**Low et al. (49)** From a minimum of 2 weeks before surgery to 30 days after discharge Average: 66 days (47-81)

				minutes later. If No then they were asked to indicate reasons. Positive feedback message was sent in all cases if 30 or more steps were logged within 15 minutes of an activity prompt.	
Low et al. [63]	See Low et al. [62]	See Low et al. [62]	See Low et al. [62]	See Low et al. [62]	From a mean of 20 days before surgery to 30 days after discharge Average: 57 days (44-92)
Martin et al. [64]	3 times per day: morning (wake time), mid-day (lunch time), evening (leisure time).	Online questionnaire pre-study for personalizing text messages (self-report on 16 personal and clinical characteristic). PA (steps). Device-based real-time data by Fitbug Orb (accelerometer) and Fitbug-compatible smartphone.	Positive reinforcement or booster messages.	Opportune moment: At each decision point, smart texts were customized to the participant, depending on if a participant was on track → positive reinforcement or not → booster message to attain their daily goal (10.000 steps).	5 weeks: Run-in (1 week). Phase 1 (weeks 2 to 3). Phase 2 (weeks 4 to 5).
McEntee et al. [65]	Daily.	PA (MVPA) Device-based measured by a wrist-worn accelerometer (ActiGraph).	Tailored feedback messages, performance feedback with reinforcement, and new exercise goals.	Prompt messages were selected in a random sequence without replication from the pool of messages and delivered daily to each individual. Adaptive goals were based on a percentile-rank algorithm using the 60th percentile of the moving average of the previous days. Differential feedback texts related to their goal	12 months.

				achievement (e.g., “You're on target! Goal met! 10 min today… Goal for 4/1 is 8 min.”).	
Nurmi et al. [66]	morning notification (new content), 5 pm notification (goal progress), not clearly specified (further behavior change tools)	Step count, heart rate. Device-based measured by a wrist-worn activity bracelet that synchronized with the app in 10-minute intervals (Xiaomi Mi Band; Firstbeat Technologies (heart rate)).	Prompts to increase motivation and provide self-regulation techniques. E.g. prompts when the user reached a goal. Further options not clearly specified.	Opportune moment: When users reached a goal, a tailored prompt is provided. When a certain pre-defined time of the day is reached tailored reminders and interactive prompts are sent out.	40-day trial including 12 three-day active study periods, 2 additional control days, and a 2-day lead-out period in which all app features were available
Pellegrini et al. [67]	Not clearly specified, short time intervals (e.g. minute).	SB (<100 counts/min). Device-based measured real-time data by a wireless accelerometer. Smartphone (Android).	Prompt to take a break from sedentary position by noise or vibration (participants preference). Question about adherence to the prompt with options: - Stand - Extend - Cannot stand - Ignore	Opportune moment: more than 20 min SB were assessed by the accelerometer → a reminder prompt was triggered encouraging the participant to stand up for at least two minutes. If participants stated they wanted to stand but did not, additional reminders were sent every 2 min.	4 weeks.
Rabbi et al. [68]	Not clearly specified, short time intervals (e.g. minute).	PA (min spent in certain activity), SB (min spent stationary), location. → Continuous life-log which clusters previous activities using machine-learning model (Gaussian Mixture Model). Device-based measured real-time data by Smartphone accelerometer and GPS, Android. Self-reported PA if no device-based measurement was possible.	Suggestions for physical activities based on user's frequent past behavior + occasional higher-calorie-burning activities.	Opportune moment: based on automated sensing (accelerometer and GPS) when participants were in specific locations (on the way to work) or sedentary for prolonged period → Prompts were sent out Daily 10 messages relating to 90% frequent activities, 10%	3 weeks.

				infrequent behaviors based on multi-armed bandit were sent.	
Rabbi et al. [69]	See Rabbi et al. (52).	See Rabbi et al. (52). Additionally, user input.	See Rabbi et al. (52).	See Rabbi et al. (52). Additionally, user preferences for the suggestions were included to allow for change in circumstances.	9 weeks (delivery ranged between 7 and 9 weeks).
Rabbi et al. [70]	Not clearly specified, short time intervals (e.g. minute).	Behavioral data and PA. → grouped behavior routines using machine-learning model (Gaussian Mixture Model). Device-based measured real-time data by Smartphone-inbuilt accelerometer and GPS. Self-reported input if no device-based measurement was possible. MyBehaviorCBP-App.	MyBehaviorCBP-generated recommendations based on their participants behaviors. E.g. “Walk for 8 more minutes near Thompson St”; “Take 3-minute walking breaks every hour”. Maximum PA of suggestions is 60 minutes.	Opportune moment: based on automated sensing (accelerometer and GPS) when participants were in specific locations (on the way to work) or sedentary for prolonged period. The app then uses a sequential decision-making algorithm (multi-armed bandit) to select and rank recommendations that are maximized to be both actionable and beneficial. → Prompts were sent out Prioritization of behaviors: - Most frequent and repeated - less intensive - small changes Suggestions also use contextual information (e.g. road names) 80% of the recommendations are easy and have been frequently followed before. 20% for exploration of other recommendations	5 weeks. 1st week – baseline 2nd–3rd week-random suggestions 4th–5th week - intervention.
Radhakrishnan et	Not clearly specified, real-	Weight monitoring (kg) and PA (steps).	Game alerts, avatar´s health	Opportune moment:	12 weeks.

al. [71]	time, short time intervals (e.g. minute).	Device-based measured real time data by Withing Go activity tracker, Withing Body smart weighting scale, Withing Health Mate app, and the Heart Health Mountain SCDG (Sensor-Controlled Digital Game).	status, messages, and incentives.	not further specified → The SCDG (Sensor-Controlled Digital Game) was tailored to participant's real-time heart failure self-management	
Robertson et al. [35]	Twice per hour.	PA (steps). Device-based measured real-time data by Fitbit Alta devices synchronized to Fitabase. Steps2Health app.	54 total messaging blocks designed to target autonomous regulation, autonomy, relatedness, and competence. Those included hyperlinks to various resources for healthy living.	Opportune moment: if certain number of steps was reached → prompt was sent including motivational messages, playful (digital) experience of destination, hyperlinks to videos for muscle strengthening, stress-reduction techniques, and positive interaction with a fictive character.	Until they reach 166.000 steps on their Fitbit devices.
Sporrel et al. [72]	Every hour from 8 am to 8 pm - Location based.	PA (frequency, duration, speed, and distance), location (GPS/ Beacons). time of the day, the day of the week, weather, and agenda availability. Device-based measured real-time data by Playful Active Urban Living (PAUL) - Basic PAUL (IG 1) - Smart PAUL (IG 2) Smart Paul app can optimize the timing of reminders with a self-learning module.	Reminder messages based on a reinforcement learning algorithm. Location-based strength exercise prompts.	Opportune moment: Pre-learned reinforcement learning model up to a max of 14 prompts per week → prompts are sent including motivational suggestions and information on progress toward their goal or on performing PA. Additionally, location-based (predetermined) strength exercise prompts containing instruction videos on the exercise were sent out (e.g. push-up in the park).	4 weeks.
Stuber et al. [73]	Not clearly specified, real-time, short time intervals (e.g. minute).	Step count, GPS data, BCT preferences measured at baseline Device-based measured real-time data	2-6 messages per day on 3 different topics: 1) feedback tailored to step	Opportune moment: Step count message is sent once per day tailored to the	12 months.

		by mobile coach app and step counter app (IG = both; CG = step counter app only)	count level 2) contextually tailored prompts near walking locations 3) behavior change advice	user's performance level. Contextual tailored messages are sent whenever the users are near preselected green spaces (max one every 4 hours). 2 messages are sent tailored to BCT preferences	
Tabak et al. [74,75]	Every two hours.	PA (counts per minute). Device-based measured real-time data by three-dimensional-accelerometer (MTx-W sensor, Xsens Technologies, Enschede, The Netherlands) and a smartphone (HTC P3600/3700).	(1) a short summary of activity behavior and (2) advice on how to improve or maintain the activity behavior. - encouraging cues (>10% deviation below reference line) - discouraging cues (>10% deviation above reference line) - neutral cues (≤10% deviation with reference line)	Opportune moment: every 2 hours → prompts were sent and tailored to the difference between the measured activity and the reference line at the moment the cue was generated.	4 weeks, first week baseline measurement to establish reference line
Valle et al. [76,77]	Not clearly specified, real-time, short time intervals (e.g. minute).	Individual-level PA data. Device-based measured via accelerometer (ActiGraph).	motivational messages, prompts to engage in PA, reinforcement or praise, questions about PA	3 prompts per week are sent at random times within 3 timeframes (9 am-1 pm, 1-5 pm, 5-9 pm)	6 months.
Van Dantzig et al. [78]	Each minute.	**Study 1:** computer activity (keyboard strokes and mouse movement). Device-based measured real-time data by own smartphone, Activity monitor, and software installed on computer. **Study 2:** SB (when the position of the 3 coordinates did not change exceeding 0.3 over 5 seconds), Device-based measured real-time data by	Study 1: Prompt (vibration + buzzing sound) to take a break from computer activity. Study 2: SB with a persuasive message recommending PA. Messages from a pool of 32: - 8 Authority messages - 8 Scarcity messages	**Study 1**: Opportune moment: whenever 30 mins of nearly uninterrupted computer activity was recorded → a short SMS containing a hyperlink was sent to the participant's smartphone, when clicked they were shown a message persuading	1 day (study 1). 6 weeks (study 2).

		accelerometer of iPhone 3G.	- 9 Consensus messages - 7 Commitment messages	them to be more active. Randomly selected from the pool. Max 3 messages a day with min 2 hours in between them **Study 2**: Opportune moment: Participants could choose time intervals, default was set to 60 min SB → prompt to take a break of 5 min, with a general daily activity goal of 50 min.	
Van Dantzig et al. [79]	Not clearly specified, real-time, short time intervals (e.g. minute).	PA (steps), time of day, location (from Bluetooth-enabled iBeacons), weather (free API of the OpenWeatherMap service), and behavioral events (participants achieved a step target or set a new step record). Device-based measured by Smartphone, wrist-worn activity tracker, Philips health watch, operating system not reported.	Prompt with audio cue. Suggestions for PA from over 500 message templates. Feedback about number of steps tailored to specific contexts.	Opportune moment: during actionable moments in personally relevant geofence zones (e.g., home, work, nature area). → prompts based on Time events, Location events, and Behavior events. Prompts were only sent if certain conditions were met (e.g., the message would only be sent between 9AM and 12AM, in rainy weather, or at a specific location).	2 calibration weeks, 1 week of intervention, and 1 week fade-out.

3.4 Effectiveness

Detailed results for intervention effectiveness are displayed in Table 3. For RCTs, 5 studies indicated effectiveness compared to a control group for PA [35,37,64,65,68], 3 studies for SB [37,63,79], and one study for pain [53]. For pre-post designed, and within-person studies, 8 studies indicated effectiveness in most outcome variables of the study for PA [38,39,46,49,57,61,67,69], 5 for SB [38,39,52,61,67], one study for pain [52], and one study for QoL [51]. Regarding the opportune moment identification, decision points and rules, most interventions which indicated effectiveness had near real time decision points on a minute to minute base, and simple decision rules depicting opportune moments when a threshold of 20-120 minutes of inactivity, SB, or computer activity was reached. Of these, the studies of Rabbi and colleagues [68,69] were the only ones which used more complex algorithms. Effectiveness was also found for longer decision point periods 2 times per hour [35], 2-3 times per day [57,64], and daily [51]. Effective interventions had an intervention duration between 3 weeks and 12 months where the majority of studies had an intervention length between 3 and 8 weeks. The other included studies which indicated no or limited effectiveness reported heterogeneous features regarding decision points, decision rules, opportune moment identifications, and complexity of algorithms as well.

Table 3: Retention, measurements and results of the interventions (IG = intervention group, CG = control group, PA = physical activity, SB =sedentary behavior, MVPA = moderate to vigorous physical activity, QoL = quality of life, LIPA =light-intensity physical activity; ↑ = significant improvement, ↓ = significant deterioration (if not otherwise described))

Author (year)	Retention	measure used, how measured, follow-up period	Significant over time or vs. group differences at p<.05 (significant/total outcomes)
Allicock et al. [36]	All participants (n = 22) completed the study. 100%.	Mean daily MVPA, daily minutes of MVPA, low/high light intensity, sedentary time, mean daily sedentary time. PA and SB: Behavioral Risk Factor Surveillance System (BRFSS) physical activity questionnaire and accelerometer (Worn 7 consecutive days). Baseline, 4 weeks (end of intervention) and 8 weeks follow-up)	**Over time:** ***PA (1/16):*** Daily minutes of MVPA ↓ CG 10.95 (SD = 9.93) min (baseline – 4 weeks) ***SB (0/8)*** **Vs. control:** ***PA (0/8)*** ***SB (0/4)***
Baumann et al. [37]	170 out of 643 completed the study. 26%.	Steps per day, daily minutes of MVPA, disruption of sedentary behavior, daily minutes of inactivity. Follow-up 8 weeks post-intervention.	**Vs. control:** ***PA (1/2):*** MVPA min/day ↑ between the 2 individualized (JITAI) IGs and the other IGs + CG from pre- to post-intervention. ***SB (1/2):*** Disruption counts/day ↑ between the 2 individualized (JITAI) IGs and the other IGs + CG from pre- to post-intervention.
Bond et al. [38]; **Thomas & Bond** [39]	30 out of 35 completed the study. 86%.	***Bond et al. (2014):*** **Primary outcome:** Change in daily time spent in sedentary behavior. **Secondary outcomes:** Light and moderate-to-vigorous PA. Device-based measured through independent measurement (separate accelerometer). No follow up. ***Thomas & Bond (2014):*** Daily number of walking prompts, walking breaks, and daily minutes of walking breaks Device-based measured through onboard accelerometer of	***Bond et al. (2014):*** **Over time:** ***PA (6/6):*** Time spent in light and MVPA ↑ in all 3 physical activity break conditions ***SB (3/3):*** ↓ in all 3 physical activity break conditions **Vs. group:** ***PA (1/6):*** Light intensity activity ↑ 3-min condition

		smartphone. No follow-up.	vs 12-min condition ***SB (1/3):*** ↓ 3-min condition vs 12-min condition ***Thomas & Bond (2015):*** **Over time:** ***PA (3/3):*** Number of daily minutes spent in walking breaks ↓ for all conditions **Vs. group:** ***PA (2/3):*** Minutes spent in walking breaks ↑ 3- and 6-min condition vs 12 min condition
Bort-Roig et al. [40]	42 out of 90 in IG. 22 out of 51 in CG. 45% total (IG: 47%; CG: 43%)	Stepping time (hours), MVPA (min), LIPA (hours), standing time (hours), sedentary time (hours), total sedentary bouts (number; <5 min, 5–10 min, 10–20 min, <20 min, >20 min, 20–30 min, 30–40 min, <40 min, >40 min, 40–60 min, >60 min, and >90 min), total sedentary time (minutes; same durations). Additionally, total time spent in light intensity and moderate-to-vigorous PA was determined by using previously validated count-to-activity thresholds. Follow-up after 12 weeks of intervention.	**Over time:** ***PA (4/20):*** MVPA (total/weekend) ↑, Stepping (work) ↑, Occupational light intensity activity ↑ ***SB (6/125):*** Sedentary breaks (non-working time 20-30min and weekend 5-10min) ↑, shorter sedentary bouts ↑ **Vs. control:** ***PA (0/20)*** ***SB (3/125):*** Number of daily breaks and time spent on short sedentary bouts (5-10/ <20 min; weekend) ↑
Brakenridge et al. [41,42]	IG: 66 baseline – 61 received intervention – 41/37 (overall/work) at 3 months – 23/21 (overall/work) at 12 months CG: 87 baseline – 86 received intervention – 68/65 (overall/work) at 3 months – 38/36 (overall/work) at 12 months 2018 IG intervention use: Frequent user (n = 9; 16 – 48 days)	**2016**: **Primary outcomes:** Average time per day spent sitting during work hours and overall. **Secondary outcomes:** Stress, physical health QoL, mental health QoL, the average time per day spent in prolonged sitting bouts (sitting time accrued in continuous bouts of 30 min or more), standing, and stepping; the number of steps per day; and the average time period between sitting bouts. PA and SB were measured objectively through ActivPAL3 activity monitor and QoL was measured subjectively via questionnaire.	**2016:** **Over time (3 months):** ***PA (1/12):*** CG: Standing, min/16h ↑ (14.6 min) ***SB (0/12)*** ***QoL (0/6)*** **Over time (12 months):** ***PA (5/12):*** CG/IG: Standing, min/10 h ↑ (CG: 39.2 min; IG: 27.4 min), Standing, min/16 h ↑

	Infrequent user (n = 16; 5 – 15 days) Limited user (n = 13; 1 - 4 days) Nonuser (n = 24; 0 days)	Follow-up after 3 and 12 months. **2018:** Time per 10 hours at work and time per 16 hours awake spent engaged in sitting, prolonged sitting (≥30 min continuously), nonprolonged sitting (<30 min continuously), standing, and stepping. Sitting and activity data were collected at baseline, 3 months, and 12 months (24/7). Objectively measured through activ3PAL activity monitor. Follow-up after 3 and 12 months.	(CG: 33.5 min; IG: 26.9 min) IG: Stepping, min/10 h ↑ (9,1 min) ***SB (8/12):*** CG/IG: Sitting, min/10 h ↓ (CG: 40.5 min; IG: 35.5 min), Prolonged sitting, min/10 h ↓ (CG: 41.3 min; IG: 45.7 min), Sitting, min/16 h ↓ (CG: 32.1 min; IG: 35 min), CG: Time between sitting bouts ↑ (1.7 min), Prolonged sitting, min/16 h ↓ (30 min) ***QoL (0/6)*** **Vs. control (3months):** ***PA (0/6)*** ***SB (0/6)*** **Vs. control (12 months):** ***PA (2/6):*** Stepping, min/16 h ↑ (20.6 min), Number of steps/16 h ↑ (846.5 steps) ***SB (0/6)*** **2018:** **Over time:** **Usage for at least 5 days:** ***PA (0/4)*** ***SB (4/6):*** Nonprolonged sitting time (work) ↑ after removal of 2 influential cases n.s. prolonged sitting time (work) ↓ Prolonged sitting time (wake) ↓ Nonprolonged sitting time (wake) n.s. but ↑ after removal of 1 influential case **Time frame activity was measured:** ***PA (0/4)*** ***SB (2/6):*** Nonprolonged sitting time (wake) ↑ Prolonged sitting time (wake) n.s. but ↓

			after removal of 1 influential case
Carlozzi et al. [43] **Wang et al.** [44]	**Carlozzi et al.:** 69 out of 70 completed the study. 99 %. **Wang et al.:** 36 out of 36 completed the study. 100 %.	HRQOL scores of caregiver strain, anxiety, and depression as a computer adaptive test throughout the 3 month home monitoring period. The final HRQOL scores for each CAT event were used in the analysis, weekly step count (not used for effectiveness). Self-reported through questionnaire within CareQOL-App. No follow-up.	**Carlozzi et al.** **Over time:** ***QoL (2/20)*** IG/CG Anxiety over time ↓ (better) **vs. control:** ***QoL (3/10):*** Caregiver Strain, Depression, and Sleep-Related Impairment ↓ (better) for IG compared to CG **Wang et al.** **HRQOL (1/9)** Caregiver strain ↓ for high JITAI frequency vs no JITAI
Compernolle et al. [45]	26 out of 26 completed the study. 100 %.	Break in sedentary behavior (within 1, 3, and 5 minutes) after feedback. Timely categorized: 6-9AM, 9AM-noon, noon-3PM, 3-6PM, 6-9 PM, 9PM-midnight. Device-based measured through Activator. No follow-up.	Out of 2628 vibrations, 379 (14,4 %; 1min), 570 (21,7%; 3min), and 798 (30,4 %; 5min) resulted in SB-breaks. **Over time (real-time):** ***SB (2/15):*** **3-minute:** Noon-3PM ↑ vs 6-9AM **5-minute:** Noon-3PM ↑ vs 6-9AM
Conroy et al. [46]	58 out of 58 completed the study. 100 %.	PA (Daily step count and MVPA). Device-based measured through Actigraph and Fitbit. No follow-up.	**Within persons:** ***PA (3/6)*** Step count and MVPA ↑ from pre-post Step count ↑ associated with number of self-monitoring prompts
Ding et al. [47]	16 out of 19 completed the study. 84 %.	Step counts during weeks 2–4 and perceived effectiveness of the app in terms of encouraging the participant to walk more. Device-based measured through in-built sensor/accelerometer (smartphone or smartwatch). Exit interview after four weeks, some data were collected at 10 pm each day (e.g. whether app encouraged them to do other activities).	**Over time:** ***PA (4/4)*** Step counts for IG and CG ↑ Self-reported effectiveness of the app to encourage them to do other physical activities for IG and CG↑ **Vs. control:**

		No follow-up.	***PA (1/2)*** Self-reported effectiveness of the app to encourage them to do other physical activities ↑
Direito et al. [48]	62 out of 69 completed the study. 90%	**Secondary Outcomes**: Daily time spent in total-, light-, and moderate to vigorous-intensity PA, and SB. PA and SB were device-based measured via the Art of Living app and the PA determinants were self-reported by validated instruments. Follow-up survey after 8 weeks.	**Over time:** ***PA (1/3):*** Time spent in light PA ↑ (2.2min/day) ***SB (0/1)***
Fiedler et al. [49]	80 out of 98 completed the study. 82 %.	MET and step count. Device-based measured through 3-axial accelerometer and smartphone. Follow-up questionnaire 4 weeks after the post measurement.	**Within-person effects (step count):** ***PA (3/3)*** Within 60/90/120 minutes answered ↑ **Between-person effects (step count):** ***PA (0/3)*** **Within-person effects (MET):** ***PA (1/3)*** Within 60minutes answered ↑ **Between-person effects (MET):** ***PA (0/3)***
Finkelstein et al. [50]	27 out of 30 participants completed the study. 90 %.	**Primary outcome:** Number of episodes of prolonged inactivity (> 2 h) per day, but only when the inactivity reminder was active. **Secondary outcome:** Step count. Device-based measured through in-built sensor / accelerometer. Eight weeks, of which four weeks with the inactivity monitor active and four weeks with the monitor inactive. No follow-up.	**Over time:** ***PA (0/3)*** ***SB (2/3):*** Two-hour slots with less than 20 steps (inactivity) during "message-on" period ↓ Inactivity Group A between periods (within-group difference) message-on vs off ↓
Freene et al. [51]	19 out of 20 patients completed the 6-week follow-up and 12 the 16-week follow-up. For missing data at the follow-up, the last value was brought forward. Therefore, all 20 participants could be	**Primary outcome:** SB (min/day), percentage of SB per day, duration of SB bouts per day, number of SB bouts per day, number of SB breaks per day. **Secondary outcome:** MVPA, light PA, vector magnitude (VM), steps per day, exercise capacity (6-min walk test, 6MWT), blood	**Over time (6weeks):** ***PA (1/5)*** 6-minute walking-test ↑ ***SB (0/5):*** ***QoL (4/4):***

	analyzed. 100 %.	pressure, quality of life (MacNew Heart Disease Health-Related Quality of Life Questionnaire, MacNew). Device-based measured through accelerometer (ActiGraph, ActiSleep) and GPS (Vire app). Follow-up after 6 weeks (end of intervention) and 16 weeks. Participants had still access to the vire app after 6 weeks, but didn´t receive any Do´s. Follow-up after 6- and 16-weeks.	↑ in all domains **QoL:** ↑ over time in all domains ***Physical Function (1/2):*** Systolic blood pressure ↓ **Over time (16 weeks):** ***PA (1/5):*** 6-minute walking-test ↑ ***SB(0/5)*** *(no significance testing due to small sample size)* Over time ↓ (Cohen´s d = 0,54) Percentage of day spent in SB ↓ **(**Cohen´s d = 0.25) ***QoL (4/4):*** ↑ in all domains ***Physical Function (1/2):*** Systolic blood pressure ↑
Fundoiano-Hershcovitz et al. [52]	981 users out of 6.098 using the app were included for the main analysis based on inclusion criteria. 14%.	Pain level and subjective posture using the numerical rating scale (NRS) from 0-10 (0, no pain – mostly slouched; 10, extreme pain – mostly upright). For all three parameters a mean value over a 7-days interval was calculated. No follow-up.	**Over time:** ***SB (1/2)*** subjective posture quality ↑ first 4 weeks and maintained afterwards ***Pain (1/2)*** Pain level ↓ (better) first 4 weeks and maintained afterwards **Additional:** Association between training duration and pain
Garland et al. [53]	63 out of 66 completed the study. 95 %.	Pain level. Self-reported near-real time data by EMAs. No follow-up.	**Over time:** **Pain (2/2)** pain level ↓ (better) for IG and ↑ (worse) for CG **Vs. control**: ***Pain (1/1***) Pain level ↓ (better) compared to control group over time
Golbus et al. [54]	214 out of 223 completed the study.	**Primary outcome:**	**Vs. control:**

	96 %.	Change in 6-min walk distance (6 months; Fitbit & Apple Watch) **Secondary outcome:** Change in 6-min walk distance (3 months; Fitbit & Apple Watch) Change in mean daily step count (6 months; Fitbit & Apple Watch) **Exploratory outcomes:** Change in mean daily step count (3 months; Fitbit & Apple Watch) Change in EuroQol Visual Analoque Scale No follow-up	***PA (1/8)*** 6 min walking distance (Fitbit) ↑ for IG vs CG from baseline to 3 months assessment ***QoL (0/1)***
Hermens et al. [55]**;** **Tabak et al.** [56]	8 out of 10 patients completed the study. 80 %.	Activity level, activity balance (%), subjective activity, exercise capacity, and health status. Device-based measured through independent measurement (separate accelerometer) and 6-min walking test to measure exercise capacity. During the three months of intervention and follow-up for one week at three months after the intervention.	*(No significance testing since data were reported for each participant)* **Over time (end of intervention):** **PA (12/32)** 5 participants ↑ activity level 4 participants ↑ activity balance 3 participants ↑ exercise capacity ***QoL (5/8):*** 5 participants ↑ health status **Over time (3-month follow-up):** **PA (10/32)** 3 participants ↑ activity level 4 participants ↑ activity balance 3 participants ↑ exercise capacity ***QoL (5/8):*** 5 participants ↑ health status The percentage of days on which goals were achieved ranged between 23 to 59% for activity levels and between 21 and 85% for balance.
Hietbrink et al. [57]	17 out of 20 completed the study. 85 %.	Mean daily step count. Device-based measured through accelerometer (Fitbit Versa 2)	**Over time:** ***PA (1/2)*** baseline to postintervention ↑ median daily step count
Hiremath et al.	16 out of 20 completed the study.	Leisure Time Physical Activity Questionnaire for people with SCI	*No significance testing due to small*

[58]	80 %.	(LTPAQ-SCI), and Wheelchair User’s Shoulder Pain Index (WUSPI). Light-, moderate- and vigorous intensity PA. Energy expenditure (kcal) and travelled distance (miles). Smartphone, smartwatch, and wheel rotation monitor. No follow-up.	*sample size* ***PA feedback (2/3):*** 4 out of 16 (light-intensity) and 3 out of 16 (moderate-intensity) PA ↑ (>+10%) ***PA feedback with JITAI (2/3):*** 6 out 19 (light-intensity) and 9 out 16 (moderate-intensity) PA ↑ (>+10%). 3 out of 16 (light-intensity) and 7 out of 16 (moderate-intensity) PA ↓ (<- 10%)
Ismail & Al Thani [59]	58 out of 58 participants completed the study. 100 %.	PA through International Physical Activity Questionnaire (IPAQ) pre-study. SB (if step count/hour < 67) and daily active time. Device-based measured through smartphone inbuilt accelerometer. No follow-up.	**Over time:** ***SB (1/2):*** MotiFit: Breaking inactivity ↑ ***PA (0/2)*** **Vs. control:** ***PA (0/1)***
Klasnja et al. [60]	45 out of 51 participants provided baseline data (88 %). 42 started the intervention (82 %). 29 provided data for follow-up (57 %).	**Primary outcome:** Average steps per day at baseline and at the end of the study. **Secondary outcome**: Steps, sitting time, standing time, and sit-to-stand transitions. Steps measured by Fitbit at weeks 1–2, weeks 15–16. Average daily step count, measured by Fitbit, over the 16-week intervention period. Pre–post comparison of activPAL step counts. Step count, measured by Fitbit, in the 30 min following each randomization. Follow-up after 16 weeks.	**Over time:** ***PA (2/4):*** Daily step count ↑ 1,866 steps Stepping time ↑ 21 min/day ***SB (0/1)***
Li et al. [61]	8 out of 8 completed the study. 100 %.	**Secondary outcomes:** PA: mean level of PA. SB: duration of sedentary activity (% of waking time), and sedentary time. The Physical Activity Scale for the Elderly (PASE). Device-based measured by wrist worn Actiwatch 2. 1 week follow-up after the 4-week intervention.	**Over time:** ***PA (2/3):*** PA ↑ at posttest (41.5 counts/min) Self-reported PA ↑ at posttest (96.2 PASE Score) ***SB (4/4):*** Sedentary time ↓ during intervention (-42.3 min) and ↓ posttest (-87.4 min) Sedentary activities (waking time) ↓ during intervention (-5.7%) and posttest (-

			8%)
Low et al.[62]	14 out of 15 participants completed the study. 93 %.	Daily step count and average SB bout duration. Device-based measured with Fitbit Versa smartwatch. No follow-up.	**Over time:** ***PA (1/3):*** Step counts ↓ from preoperative to inpatient recovery ***SB (1/3):*** SB bouts ↑ from preoperative to inpatient recovery
Low et al. [63]	23 out of 26 completed the study. 88 %.	QoL, daily step count and average SB bout duration. Device-based measured with Fitbit Versa smartwatch and QoL via questionnaire. No follow-up.	**Over time:** ***PA (1/2):*** Step counts ↓ from preoperative to inpatient recovery ***SB (1/2):*** SB bouts ↑ from preoperative to inpatient recovery ***QoL (3/6):*** QoL ↓ from preoperative to inpatient recovery depressive symptoms ↑ (worse) from preoperative to inpatient recovery physical symptoms ↑ (worse) from preoperative to inpatient recovery **vs control:** ***PA (0/1)*** ***SB (1/1):*** maximum overall SB bouts ↑ in the intervention compared to control group. ***QoL (0/3)***
Martin et al. [64]	47 out of 48 participants completed the study. 98 %.	PA through International Physical Activity Questionnaire (IPAQ) pre-study. **Primary outcomes:** Mean change in daily step count and attainment of the step goal. **Secondary outcome:** Changes in daily activity time and aerobic time. Device-based measured through Fitbug Orb accelerometer.	**Over time:** **Phase 1** ***PA (0/3)*** **Phase 2** ***PA (3/3):*** Daily steps (37% increase) ↑ Total activity time ↑ (21 min/day)

		No follow-up.	Aerobic time ↑ (13 min/day) **Vs. no texts:** ***PA (3/3):*** Daily steps ↑ (+2534 steps/day) Aerobic time ↑ Total activity time ↑ **Vs. blind:** ***PA (3/3):*** Daily steps ↑ (+3376 steps/day) Aerobic time ↑ Total activity time ↑
McEntee et al. [65]	512 out of 512 completed the study. 100 %. 128.993/157.285 (82%) accelerometer observations.	Likelihood of any MVPA, Daily MVPA bout minutes. Device-based measured using a wrist-worn accelerometer. No follow-up.	**Over time:** **PA (2/2)** likelihood of any MVPA ↑ in all intervention groups Daily MVPA bout minutes ↑ in all intervention groups **Vs. control:** **PA (1/2)** likelihood of any MVPA from baseline to intervention adaptive goals ↑ relative to static goals.
Nurmi et al. [66]	15 out of 15 completed the study. 100 %. A total of 88.3% (530/600) of usable data points were recorded.	Daily steps. Device-based measured using a wrist-worn accelerometer. No follow-up.	**Within-person vs. control condition** **PA (0/2)**
Pellegrini et al. [67]	8 out of 9 completed the intervention. 89 %.	Proportion of the day spent sedentary, proportion of the day spent in light PA, and MVPA, breaks/day in sedentary time, break duration, break intensity. Device-based measured through independent measurement (separate accelerometer). One month, which was during the intervention period.	**Over time:** **PA (1/3)** Light PA ↑ **SB (3/3)** Sedentary time ↓ Breaks/day in sedentary time ↑ Break duration ↓ **Within-person (light PA):** **PA (7/8)** 7/8 participants ↑ time spent in light

			physical activity.
Rabbi et al. [68]	17 out of 17 completed the 3-week period. 100 %.	Walking trends and walking time. Device-based measured by smartphone-inbuilt GPS. No follow-up.	**Vs. control:** ***PA (2/2):*** Walking trends ↑ (IG: 7 out of 9) Walking time ↑ (IG: +10 min)
Rabbi et al. [69]	16 out of 16 completed the study. 100 %.	Behavior change (calorie loss in exercise) from participants' logs of daily activity. Self-report. Minutes of walking per day. Device-based measured by smartphone-inbuilt GPS. No follow-up.	**Vs. control:** ***PA (2/2):*** Minutes of walking per day ↑ Calories burned through non-walking exercises per day ↑
Rabbi et al. [70]	10 out of 10 completed the study. 100 %.	Number of minutes spent walking per day, number of minutes spent in nonwalking exercises per day. Device-based measured with smartphone inbuilt sensors. Pain level from 0 to 10. Self-reported in daily evening survey. No follow-up.	**Vs. control:** ***PA (1/2):*** Daily walked minutes ↑ ***Pain (0/1)***
Radhakrishnan et al. [71]	30 out of 38 participants attended the 12-week surveys (79 %) and 27 remained in the 24-weeks survey (71 %).	Cumulative steps for each day and average steps over 6 and 12 weeks, heart failure-related functional status, and QoL. PA behavior was device-based measured through Withings Go sensor. Data about functional status and QoL were obtained with the Kansas City Cardiomyopathy Questionnaire (KCCQ). Surveys were completed at 6, 12 and 24 weeks (follow-up) after baseline survey.	**Over time:** ***PA (1/2):*** *no significance testing* Steps: Modest ↑ IG; Modest ↓ CG 6th to 12th week ***QoL (5/6):*** ↑ (baseline to 6/12/24 weeks) in both groups except baseline to 6 weeks for IG ***Physical Function (2/6):*** HF functional status ↑ after 6 weeks in IG HF functional status ↑ after 24 weeks in CG
Robertson et al. [35]	75 out of 78 completed the study. 96 %.	PA pre-study and for MVPA: Godin Leisure-Time Exercise Questionnaire. PA: MVPA (self-reported), and step count device-based measured by Fitbit. PA pre-study and for MVPA: Godin Leisure-Time Exercise Questionnaire. 28 days follow-up after the intervention (4 weeks).	**Over time:** ***PA (5/9):*** Self-reported: ↑ group-by-time interaction in favor of IG (52% ↑) Step count: ↑ group-by-time interaction ↑ for IG during the intervention Result extended in the follow-up.

Sporrel et al. [72]	20 out of 23 completed the study. 87 %. 9 out of 12 (BasicPaul) were analyzed. 75 %.	MVPA. Device-based measured through smartphone-inbuilt accelerometer (ActiLife), and pre-posttest PA measures with additional hip-worn accelerometer (ActiGraph GT3X+). Follow-up questionnaire 1 week after intervention.	**Over time:** ***PA (0/1)*** **Vs. control:** ***PA (0/1)***
Stuber et al. [73]	361 out of 421 completed the study. 86 %.	Daily step count. Device-based measured through smartphone's built-in pedometer or accelerometer. No follow-up.	**Vs. control:** ***PA (0/1)***
Tabak et al. [74,75]	30 out of 34 completed the study. 88 %.	Number of steps per day and health status (2014b). Activity counts per minute (cpm) (2014c). Device-based measured through MTx-W 3D accelerometer, Yamax Digiwalker 200 (pedometer) and subjectively through Multidimensional Fatigue Inventory (MFI-20). No follow-up.	**2014b:** **Over time:** ***PA (0/6)*** ***QoL (1/2)*** Health status ↑ IG **Within-person (1/13 IG; 3/15 CG)** 1 patient (IG) ↓ health status. 3 patients (CG) ↓ health status. **2014c:** **Over time:** ***PA (1/3):*** PA level after corrected for reactivity ↑ on a group level. ***PA (4/33): Within-person*** Activity level ↑
Valle et al. [76,77]	**Valle et al. (effect):** 251 out of 280 completed the study. 90 %. **Valle et al. Physical:** 236 out of 280 delivered accelerometer data. 84 %. 246 out of 280 delivered self-reported data. 88 %.	Total PA, MVPA, steps per day, SB. Device-based measured through wrist worn accelerometer and self-reported data via questionnaires. 12 months follow-up.	**Valle et al. (Effect):** **Over time:** **PA (9/14)** Accelerometer: total PA IG ↑ MVPA IG and CG ↑ steps IG ↑ Self-report: total PA IG and CG ↑ MVPA IG and CG ↑ light PA IG ↑ **SB (0/8)**

			Vs. control: **PA (0/7)** after removal of outliers ↑ accelerometer based MVPA in IG vs CG **SB (0/4)** **Valle et al. (Physical):** **Over time:** **PA (8/14)** Accelerometer: baseline-12 months: MVPA IG and CG ↑ 6 months-12 months: steps IG ↓ Self-report: baseline-12 months: total PA IG and CG ↑ MVPA IG and CG ↑ light PA IG ↑ **SB (1/12)** Accelerometer: 6-12 months: SB ↑ (worse) **Vs. control:** **PA (1/7)** self-report: ↑ total PA in IG vs CG baseline to 12 months **SB (0/3)**
Van Dantzig et al. [78]	86 out of 86 completed the study. 100 %.	Computer activity (proxy for sedentary behavior) and physical activity (calories) during the 30 mins before a text message were compared with computer activity and physical activity during 30 mins after the text message. Device-based measured through independent measurement (separate accelerometer); computer activity through specially installed software. No follow-up.	**Study 2:** **Over time:** ***PA (1/1):*** Calories ↑ ***SB (1/1):*** Computer activity ↓ **Vs. control:** ***PA (1/1):***

			Calories in IG ↑ ***SB (1/1):*** Computer activity ↓ **Over time x vs. condition:** ***SB:*** Computer activity IG (10.0 min) ↓ compared to CG (5.9 min)
Van Dantzig et al. [79]	60 out of 70 completed the study. 86 %.	Average daily step count. Device-based measured through independent accelerometer. Collected during a 2-week calibration period, 1-week intervention period and 1-week fade-out period.	Each group was divided into three clusters: cluster 1: steps<=6500, cluster 2: 6500 < steps<=9500, and cluster 3: steps> 9500. **Over time:** **PA (4/18)** Cluster 1: CG coaching ↑ vs calibration and fadeout IG coaching ↑ calibration. Cluster 2: IG coaching ↑ vs calibration and fadeout.

3.5 Study quality

Table 4: Study quality of included studies based on the Quality Assessment Tool Effective Public Health Practice Project. Green indicates a strong rating, yellow a moderate rating, and red a weak rating of the respective category.

Autor (year)	Selection Bias	Study Design	Confounders	Blinding	Data Collection methods	Withdrawals and drop-outs	Global Rating
Allicock et al. [36]	Yellow	Green	Green	Red	Green	Green	Yellow
Baumann et al. [37]	Red	Green	Green	Green	Yellow	Red	Red
Bond et al. [38]	Yellow	Yellow	Green	Red	Yellow	Green	Yellow
Bort-Roig et al. [40]	Yellow	Green	Red	Red	Yellow	Red	Red
Brakenridge et al. [42]	Yellow	Green	Green	Red	Yellow	Red	Red
Brakenridge et al. [41]	Yellow	Yellow	Green	Red	Yellow	Red	Red
Carlozzi et al. [43]	Yellow	Yellow	Green	Red	Yellow	Green	Yellow
Compernolle et al. [45]	Yellow	Red	Green	Red	Yellow	Green	Red
Conroy et al. [46]	Yellow	Yellow	Yellow	Red	Yellow	Green	Yellow
Ding et al. [47]	Red	Green	Red	Red	Red	Green	Red
Direito et al. [48]	Red	Yellow	Green	Red	Yellow	Green	Red
Fiedler et al. [49]	Yellow	Yellow	Green	Yellow	Yellow	Green	Green
Finkelstein et al. [50]	Yellow	Green	Green	Red	Green	Green	Yellow
Freene et al. [51]	Yellow	Yellow	Green	Red	Green	Yellow	Yellow
Fundoiano-Hershcovitz et al. [52]	Green	Yellow	Red	Red	Yellow	Yellow	Red
Garland et al. [53]	Yellow	Green	Green	Yellow	Yellow	Green	Green
Golbus et al. [54]	Red	Yellow	Green	Red	Yellow	Green	Red
Hermens et al. [55]	Green	Yellow	Green	Red	Red	Green	Red
Hietbrink et al. [57]	Yellow	Yellow	Green	Red	Yellow	Green	Yellow
Hiremath et al. [58]	Yellow	Yellow	Yellow	Red	Red	Green	Red
Ismail & Al Thani [59]	Yellow	Green	Red	Red	Red	Green	Red
Klasnja et al. [60]	Yellow	Yellow	Green	Red	Yellow	Red	Red
Li et al. [61]	Yellow	Yellow	Green	Red	Red	Green	Red
Low et al.[62]	Yellow	Yellow	Red	Red	Red	Green	Red
Low et al. [63]	Yellow	Green	Yellow	Red	Yellow	Green	Yellow
Martin et al. [64]	Yellow	Green	Green	Red	Red	Green	Red
McEntee et al. [65]	Yellow	Yellow	Yellow	Red	Yellow	Green	Yellow
Nurmi et al. [66]	Yellow	Yellow	Red	Red	Yellow	Green	Red
Pellegrini et al. [67]	Yellow	Yellow	Red	Red	Red	Green	Red
Rabbi et al. [68]	Red	Green	Yellow	Yellow	Red	Green	Red
Rabbi et al. [69]	Yellow	Yellow	Red	Red	Red	Green	Red

Rabbi et al. [70]							
Radhakrishnan et al. [71]							
Robertson et al. [35]							
Sporrel et al. [72]							
Stuber et al. [73]							
Tabak et al. [56]							
Tabak et al. [74]							
Tabak et al. [75]							
Thomas & Bond [39]							
Valle et al. [76]							
Valle et al. [77]							
Van Dantzig et al. [79]							
Van Dantzig et al. [78]							
Wang et al. [44]							

The quality assessment showed that four studies achieved a “strong” global rating (Table 4). 15 studies were rated “moderate” and all the other studies were judged with two or more “weak”-ratings. Most common weak ratings in 38 and 17 out of 45 were related to context of blinding and data collection methods respectively.

4 Discussion

The objective of this study was to provide a systematic overview about the concept of JITAIs and to explore important parameters in KOA management. In total, 45 studies with 38 different JITAIs focusing on the outcomes PA, SB, pain, QoL, physical function, and stiffness were analyzed in this review. While the majority of studies investigated PA and SB, physical function, pain, and QoL were addressed by few studies and the parameter stiffness was not included in any study indicating a research gap. Reporting and use of the key facets of JITAIs [27] along with the methodology and aspects of study design of the included studies were heterogeneous. The best evidence for effective JITAIs exists for device-based measured PA and SB employing frequent decision points and simple algorithms to deliver prompts after a period of physical inactivity or SB. This can be translated to the use case of KOA and accompanied by a specific knee load management to improve KOA treatments with JITAIs in the future.

4.1 Just-in-time adaptive interventions in the context of PA, SB, pain, stiffness, physical function and QoL

Overall intervention effectiveness is hard to pinpoint and not comparable between studies due to heterogeneous study design, outcome measures, number of statistical comparisons, time windows, sample size, and focus on within- or between-person effects. Stratifying the results by study design, 5 out of 14 RCTs found the intervention to increase PA effective and 3 studies had a positive effect on SB, and one study improved the pain level of participants. Pre-post study designs as well as the within-person studies found an increase in PA in 8 studies, a reduction of SB in 5 studies, a reduction of pain in one study, and one study positively influenced QoL. No evidence of effectiveness in studies for physical function outcomes were found. To obtain more results about causation under consideration of time-varying effects, it is important to increase the number of micro-randomized trials in the future [60] and focus on the state of receptivity of participants. This will also provide more information about what works in which situation and for whom and will help to provide valuable information to advance the field of JITAI research.

Although the studies showed a high degree of heterogeneity, some patterns can be observed. For example, decision points with a shorter period of time (e.g., minute to minute) and an intervention duration of 3 to 8 weeks have shown good evidence for intervention effectiveness. Here, it is important to add that intervention duration and timing of decision points has to be viewed together to avoid overburdening participants and to keep the content engaging. Otherwise, JITAIs run at a high risk of disengagement [85] that can hinder behavior change. The optimal dose for these parameters has still to be fully explored. Conroy and colleagues [46] point out that self-monitoring prompts, but not behavioral feedback, show signs of a dose-response association with physical activity volume in JITAIs. This is an important finding that should be followed up by further studies. The included studies provide limited information regarding the long-term effectivity of JITAIs for behavior change. Of the 15 studies that included a follow-up measurement, 3 studies showed significant benefits of the intervention for QoL [51,55,56] and 2 studies for PA [76,77]. This is not surprising, as JITAIs are an upcoming topic and still focus mainly around the opportune moment identification, feasibility, usability, and technological challenges of the intervention [27]. In addition, decision rules that represent opportune moments when a threshold of 20-120 minutes of inactivity, SB or computer activity has been reached, resulted in behavior change. Here, shorter timeframes might be more useful to break SB as Thomas & Bond [39] have shown that opportune moments after 30 minutes of being sedentary are more effective than longer decision points of 60 and 120 minutes.

PA or SB was monitored in all significant studies by the smartphone application or by an accelerometer. In addition, prompts were used by each study as an intervention option to interrupt SB, send encouraging messages, give suggestions to increase PA or to send useful and interesting links/information. For example, Freene et al. [51] sent prompts in the form of Do's to help change behavior and learn a new behavior. The unique feature of this JITAI was that the Do's were sent based on a variety of tailoring variables namely if participants showed a low score in PA, social opportunity, and variety on three consecutive days. Although it was not possible to positively influence PA or SB, the parameter QoL could be increased in four different domains, both after 6 and after 16 weeks. This result could mean that variety and social opportunity can be more easily influenced by Do's than PA. Another reason could be that shorter decision points are more effective for PA while for QoL longer decision points like days are sufficient.

Importantly, Ding and colleagues [47] highlighted that 43% of the supposed "just-in-time messages“ were not perceived as just-in-time by the participants. This is problematic as sending prompts at moments when participants do not have the opportunity to change their behavior will not lead to the desired effect and might even lead to disengagement with the intervention [26]. The importance of an adequate opportune moment identification has also been highlighted by previous research [25,27] and should be assessed by future JITAI studies. This can be done by a repeated short ecological momentary assessment which then can also inform and adapt the timing of the intervention and improve adherence and thus behavior change. One example is the study of Rabbi and colleagues [70] who included participants preferences into the opportune moment identification which allowed their algorithm to e.g. adapt learned opportune moments that were no longer valid.

Shortcomings of the included studies include the overall weak study quality and the mainly simple intervention design that is not optimized for opportune moment identification as it seldomly includes the state of receptivity of participants but focus on the vulnerability. This should be the focus of future studies that consider participants to e.g. not initiate a JITAI trigger when the tailoring variables (e.g. calendar or user-preferences) indicate that the participant is not receptive [86]. In this context, the role of contextual factors assessed by GPS or EMA [87] are important aspects that are included in a few studies [36,51,54–57,59,60,68–70,72,78,79] and point to the feasibility of such interventions. If interventions including context variables are more effective than those that do not, cannot be answered by this review as no clear pattern emerges. The additional information provided by these studies is nonetheless very helpful for future interventions and should be explored further including EMA studies on this topic [88]. The blinding of participants was the main issue for the quality assessment. While it is difficult to blind participants in mobile health research, micro-randomization makes this process easier and has a lot of additional benefits as discussed before. Furthermore, the includes studies scored weak to moderate for selection bias. Here, more diverse samples and non-convenient samples are required in future research to strengthen the evidence-base and the generalization of JITAI study results. Additionally, future studies should test different sets of decision points, tailoring variables, decision rules and intervention options within one study to improve the current literature on what works for whom and how. This would improve the evidence base for future JITAI interventions in different populations and settings.

4.2 Specific considerations for the transfer of the finding to the use case of KOA

As a recommendation, the WHO [17] states that a healthy lifestyle should be cultivated and that maintaining a normal body weight plays an important role to prevent OA and control the disease progression. Here, PA and SB are behavioral variables which influence pain, physical function, stiffness, and QoL of patients with KOA [6–10]. As a consequence, PA and SB can be used to a certain extent as proxy variables to target the distal outcomes pain, physical function, stiffness, and QoL. However, despite the fact that appropriate mechanical stimuli are needed for promoting optimal joint function [5] more PA is not necessarily better for patients with KOA [89] and can even support the development of the disease [62]. In particular, it is recommended to reduce overuse of joints by refraining from PA that contain start–stop movements, rapid changes in direction, intense jumps and landings [90].

To design a JITAI for KOA, specific tailoring variables have to be considered. Based on our findings, starting points for intervention studies could include device-based measured PA and SB variables in addition to time, location, and pain scores assessed as user-input through a mix of event-based and random sampling using ecological momentary assessments [68] to tailor the intervention to participants needs. From a theoretical perspective, additional JITAIs for stiffness would be very helpful to provide an evidence base for the creation of a JITAI for KOA. A further important tailoring variables that has not been found by this review is the knee load. Here, body worn measurement technologies such as orthopedic shoe insoles or knee braces with built-in sensors to measure the forces exerted on the knee joint are promising developments for interventions which can adapt the minimum and maximum load limit to each participant and situation [91–94]. Wearable joint monitoring technologies may also help indirectly assess varying levels of joint stiffness. For example, by quantifying the joint range of motion [95] or assessing relationships between gait biomechanics and fluctuations in KOA-symptoms, valuable data can be gained [96]. Additionally, EMA could be used for a targeted assessment of specific symptoms, such as morning stiffness. Pain can also be assessed as user-input through a mix of event-based and random sampling using EMAs [68]This would allow to tailor the JITAI to e.g. user specific self-reported amount of pain, knee load under consideration of certain conditions and allow for a highly individualized approach.

A further important intervention method found by this review are educational prompts. These prompts could contain informative facts to educate the user on how to move and exercise appropriately [17] tailored to e.g. their PA, SB, pain, and stiffness. While conventional JITAIs mainly aim to increase PA through classical exercise, JITAIs that focus on the therapy of specific diseases, such as KOA, could use therapeutic exercises and tasks to promote health behavior. For example, it has already been shown that a combination of muscle strengthening and range-of-motion (ROM) exercises resulted in a significant improvement in OA-symptoms in the long term [3,97]. Moreover, muscle strengthening was associated with reduced pain and increased function in patients with KOA [98]. These exercises could be encouraged in appropriate moments through the use of a JITAI. In the deployment of digital interventions and JITAIs, it is imperative to account for the technological prerequisites and potential barriers for participants and practitioners. This consideration becomes especially significant when the intended audience includes older patients, exemplified by those suffering from KOA, as underscored in the research conducted by Hinman and colleagues [23].

4.3 Designing a JITAI for the use case KOA

To design a JITAI for KOA several important decisions need to be made. First, the outcome parameters need to be selected. Second, the device for JITAI delivery and assessment of tailoring variables needs to be chosen. Third, tailoring variables, decision points, intervention options, and decision rules need to be defined.

Derived from previous research and the results of this review, the aim of a promising JITAI is to target the proximal outcomes PA, and SB in accordance with the recommendations of KOA therapy [17]. This should result in positive developments in the distal outcomes pain, physical function, stiffness, and QoL. Here, smartphones, accelerometers, or KOA specific measurement technologies can be used for the intervention and the evaluation of effectiveness. In addition to device-based measured PA and SB, ecological momentary assessments can be used to gather information via user-input about loads of previous activities or provide conclusions about parameters such as pain and stiffness. The potential of ecological momentary assessments for understanding individual behavior is indispensable [99,100] and two studies including EMA showed significant pain reduction of participants [52,53]. In addition, the use of sensors for load management would be very useful to provide device-based feedback of knee-load and adapt the intervention accordingly to prevent an overloading of the knee joint [93,94]. Further approaches could also include smartphone data about the weather, calendar, or the user's location to improve the opportune moment identification [27].

The time span in which the decision points are to be made should be of shorter duration, as emerged from the results. Decision points every minute proved to be useful and offer quick adaptation to changing situations. That is especially important to avoid too high knee load in near real-time and to break up SB. Prompts to boost overall PA and deliver knowledge could use longer decision points to avoid overburdening the participants [26].

The best evidence regarding intervention options exists for prompts to break prolonged SB or physical inactivity. That is also a relevant parameter for KOA [9] and could be linked with positive reinforcement messages or booster messages, which showed success in the study by Martin and colleagues [64]. Additional intervention options include maintaining an optimal amount of PA while avoiding overloading of the OA affected knee. This could be achieved by continuously tracking and displaying the estimated knee load (e.g. using knee specific feedback technology [94,101]) on the smartphone and prompting participants in near real-time if the knee load reaches a critical individual level. To avoid insufficient PA of participants, daily PA goals could be used. Here, daily prompts with positive reinforcement messages could prompt participants in the morning if they failed to achieve the PA goal of the previous day.

In the next step, the decision rules can be formulated. Based on the study by Thomas and Bond [39], interrupting SB after 30 minutes is promising which is also linked to improved metabolic health [102]. Here, it is important to consider that the prompt really appears in an opportune moment [103] to avoid overburdening participants especially if such a short time frame is chosen. One option to solve this is to allow users to choose time frames when such triggers occur, enable them to mute the triggers for a certain period of time, or by using more complex decision-making algorithms based on machine learning principles that implement the availability of the user (e.g. including calendar). Rules for accompanying positive reinforcement messages and educational information about why PA is useful in the topic of KOA should be formulated to have a maximum number of messages per day. There is also the possibility of including movement recommendations to go for a walk in the nearest park or to explore new places. Decision rules for the optimal amount of PA should only send prompts if participants are closing in on their critical knee load level or if inappropriate kinds of PA like reoccurring jumps are detected to avoid making participants hesitant about PA. These prompts should always be followed by an explanation for the prompt and recommendations for the future. As these prompts are very hard to define, users should have the option to adapt the prompt in correspondence with a health professional until the prompt is appropriately defined.

Finally, an important consideration for the design of a JITAI in the context of KOA is co-designing of the intervention. Mrklas and colleagues [104], describe a frequently occurring problem within the topic of mHealth apps. Users, in this case people with KOA, are usually not involved in the development of the JITAI-app. That can lead to interventions which are not a good fit for the target population. For better individualization, it is crucial to include the opinions and experiences of those affected. This can help to positively influence the user engagement, which has an impact on the effectiveness of a JITAI as been highlighted by previous research [105–107]. The framework by Choi and colleagues [103] addresses this issue and could be used for a higher user-friendliness and thus a higher engagement in the design of JITAIs.

4.4 Limitations and Strengths

Strengths of this review include the detailed search, which has a high number of results within the four databases. Furthermore, the chance of finding all relevant articles was increased by examining useful articles for further studies and thus we were able to include 45 relevant papers. The examination of multiple outcome variables for relevant for KOA patients yields a good fit for a special use case while also providing an overview of JITAIs for health behavior change in general as it was not focused on a specific group of participants.

Limitations of this review include that the terminology and structure of a JITAI has not yet been defined based on a common definition which hinders screening of eligible articles. A uniform framework for future JITAIs would be of great advantage and would increase comparability [28]. Therefore, this review is oriented and structured based on a JITAI framework [27]. In general, most of the included JITAIs have shown a very high heterogeneity, a low number of participants, and includes preliminary studies which makes it difficult to draw conclusions. In addition, either no studies or only very few studies were found that refer to the parameters physical function, stiffness, pain and also QoL which limits the explanatory power regarding these parameters. In order to make evidence-based statements, further outcome specific and high quality JITAI studies are needed. Finally, body weight and the associated load on the joints are a decisive factor in KOA [108] which has not been addressed by this review to maintain a concise focus.

5 Conclusions

In summary, a variety of JITAIs can be identified that represent interesting and promising results for behavior change in physiological health outcomes. Although a high degree of heterogeneity in the results were found, patterns have been identified that are associated with intervention effectiveness. Using frequent decision points, device-based measured tailoring variables accompanied by user input, intervention options tailored to user-preferences, and simple decision rules showed the most promising results in previous studies. Transferring this knowledge to the use case of KOA can result in a JITAI to break SB, increase PA, and maintain an optimal knee load for health benefits of patients. Future JITAIs should be oriented towards a uniform structure and terminology, employ micro-randomized interventions to be able to draw better conclusions, integrate new technological aspects like sensors for the assessment of knee load, and explore optimal dose-response mechanisms and contextual factors that are linked to intervention effectiveness.

List of abbreviations

JITAI – just-in-time adaptive interventions
KOA – knee osteoarthritis
mHealth – mobile health

OA – osteoarthritis

PA – physical acitivity

QoL – quality of life

SB – sedentary behavior

Declarations

Availability of data and materials

All data generated or analysed during this study are included in this published article [and its supplementary information files].

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

JF & MB conducted the literature search, the article screening, and data extraction. MB and BS assessed the study quality. Interpretation of the data, and conducting of the first draft of the manuscript was done by JF & MB with valuable comments from BS. BS, SS, & AW revised the manuscript. All authors read and approved the final manuscript.

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Supplementary Files

Multimedia Appendixes

Search Strategy.
URL: http://asset.jmir.pub/assets/34d698525a9b901ac0184474e135de5c.docx

Theoretical Foundation and BCTs.
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CONSORT (or other) checklists

PRISMA checklist.
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