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Review

eHealth interventions to promote objectively measured physical activity in community-dwelling older people

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ABSTRACT

eHealth solutions are increasingly being applied to deliver interventions for promoting an active lifestyle in the general population but also in older people. Objective assessment of daily physical activity (PA) is essential to accurately and reliably evaluate the effectiveness of such interventions. This review presents an overview of eHealth interventions that focus on promoting PA in community-dwelling older people, and discusses the methods used to objectively assess PA, and the effectiveness of the eHealth interventions in increasing PA. The twelve eHealth intervention studies that met our inclusion criteria used a variety of digital solutions, ranging from solely the use of an accelerometer or text messages, to interactive websites with access to (animated) coaches and peer support. Besides evaluating the effectiveness of an intervention on objectively assessed PA, all interventions also included continuous self-monitoring of PA as part of the intervention. Procedures for the collection and analysis of PA data varied across studies; five studies used pedometers to objectively assess PA and seven used tri-axial accelerometers. Main reported outcomes were daily step counts and minutes spent on PA. The current evidence seems to point to a positive short-term effect of increased PA (i.e. right after administering the intervention), but evidence for long-term effects is lacking. Many studies were underpowered to detect any intervention effects, and therefore larger studies with longer follow-up are needed to provide evidence on sustaining the PA increases that follow eHealth interventions in older people.

1. Introduction

Continuing or commencing an active lifestyle with ageing is associated with health benefits. It is well-documented that higher levels of daily physical activity (PA) are associated with better physical and mental well-being in older people [1–3]. Adopting an active lifestyle at old age has also shown strong positive effects for older people, such as improved functioning [4], reduced fall risk [5], and improved quality of life[6]. In addition, physical *in*activity can boost physical decline as a result of ageing [7]. Given its potential for counteracting or slowing down detrimental outcomes, interventions for promoting an active lifestyle are widely considered in aging populations [8].

Over the past decades, the use of information and communication technology (ICT) to deliver lifestyle interventions has grown exponentially. The use of ICT solutions in healthcare services is often called electronic health or eHealth [9]. eHealth interventions that use electronic devices, such as computers, smartphones or tablets, for promoting an active lifestyle have shown positive results on PA in the general population [10], as well as in older people [9]. eHealth interventions are presumed to have great potential to increase access to interventions, increase compliance, lessen the burden on healthcare staff, and are highly scalable. Moreover, the use of a digital environment allows for delivery of continuous feedback and application of additional behaviour change techniques within the technology [11]. It further facilitates the tailoring of the intervention to the individual [12]. Those aged ≥55 years may be more familiar with using electronic devices and wearable technology than previous generations [13], and prior evidence has shown that this generation finds electronic devices promoting PA acceptable [14].

When evaluating the health benefits of lifestyle interventions for older people, it is essential to consider theories underlying the intervention to understand working mechanisms [15]. Besides piloting

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feasibility of newly developed eHealth interventions in a small sample, evaluating intermediate outcomes related to health, such as PA, is considered crucial to prove effectiveness and establish the causal pathways of long-term health benefits [15]. A recent systematic review showed that eHealth lifestyle interventions are effective in promoting PA in people above 50 years; however, the majority of studies in this review measured PA self-reported by questionnaires [9]. Although questionnaires are inexpensive, quick and easy to administer, they are prone to recall bias, might lead to variable and socially desirable answers and generally do not assess light PA or ordinary activities in daily life [16,17]. Questionnaires therefore do not provide a very accurate reflection of a person's daily PA. Increased availability of wearable devices, such as pedometers or inertial sensors, allows collection of objective PA data in daily life [18]. Pedometers count steps while walking, whereas inertial sensors collect and store data over longer periods, later analysed to extract multiple features of PA. Inertial sensors, particularly tri-axial accelerometers, have shown better reliability in capturing daily PA than pedometers and uniaxial accelerometers due to their ability to detect light PA [19].

This review presents an overview of recent eHealth interventions for promoting PA in community-dwelling older people with objective measurements of PA (i.e. by pedometer, uni-axial or tri-axial accelerometers). We discuss the eHealth interventions developed for promoting sPA in the older target population, as well as the employed methods to assess PA objectively. Finally, we discuss the effectiveness of the interventions on PA behaviour.

2. Methods

For this narrative review, we followed the guidelines for database search, selection of studies and data extraction from Cochrane [20]. We searched PubMed (from January 1990 to January 2018) with key search terms and synonyms for "older people", "telemedicine", "exercise", "ambulatory monitoring", and "randomized trials" (see Supplementary Table 1 for the search syntax). Studies were included in the current review if they: 1) included community-dwelling people with a mean or median age > 55 years; 2) evaluated an intervention that aimed to promote physical activity and/or reduce sedentary behaviour; 3) used a computer, tablet, smartphone, or smartwatch to deliver the main component of the intervention; 4) used objective assessment of the amount of physical activity to evaluate the effectiveness of the intervention; and 5) had a randomised trial design. We excluded studies that focused on a target group with a specific disease (e.g. stroke or Parkinson's disease).

3. Results

3.1. eHealth interventions for promoting physical activity

Twelve different studies met our inclusion criteria [21–32] (Table 1 for details and Fig. 1 for a flowchart of the search). Sample sizes of studies varied from 40 [28] to 263 [21], with eight out of twelve studies including < 100 participants. The ICT modalities that were used by studies to deliver the interventions differed considerably, and four studies compared multiple interventions with one control condition [23,24,29,30]. The study by Thompson and colleagues simply compared wearing a smartwatch accelerometer, which provided feedback on PA, to a control condition [31], whereas the other studies evaluated more extensive eHealth solutions for changing PA behaviour. Six studies used an interactive website that participants could use for goal-setting, planning, self-monitoring progress and receiving feedback [23,24,26,29,30,32]. Three studies used an application on a tablet for this purpose [21,25,28] and two of these studies also used a smartphone application [27,29]. Other ICT components employed by studies consisted of sending text messages [22,29], video clips [27], and tools for peer interaction [23–25,28,30]. Wijsman et al. [32] provided

Table 1
Description of populations and interventions of included studies, stratified by method of data collection for outcome of objective assessment of physical activity.

Study	Sample size	Study population	ICT-based intervention components	Control condition
Pedometer assessment				
Bickmore et al. [21] USA	263	Inactive people ≥65 years	2 months pedometer + tablet with animated coach	Pedometer
Kim & Glanz [22] USA	45	People 60–85 years	6 weeks pedometer + 3 motivational text messages per day on 3 days per week	Pedometer
Kullgren et al. [23] USA	92	People ≥65 years who want to be more physically active	16 weeks pedometer + website for peer forum	Pedometer
Rowley et al. [24] USA	170	Insufficiently active people 55–80 years	12 weeks pedometer + interactive website including peer forum	Waitlist (usual practice)
Uni-axial accelerometer assessment				
Lewis et al. [25] USA	40	Inactive people 55–74 years	12 weeks accelerometer for step counting + tablet with application including peer support + 1 counseling session	Pedometer + 1 counselling session
Tri-axial accelerometer assessment				
Cadmus-Bertram et al. [26] USA	51	Inactive post-menopausal women	6 weeks accelerometer + web interface + 1 follow-up phone call	Pedometer
Fukuoka et al. [27] USA	61	Inactive people ≥35 years, at risk of type 2 diabetes mellitus	20 weeks pedometer + smartphone application with daily messages/videoclips	Pedometer
Lyons et al. [28] USA	40	Inactive people 55–79 years	12 weeks accelerometer + tablet application including peer support + 1 session + weekly phone calls	Waitlist (usual practice)
Martin et al. [29] USA	48	Inactive people 18–69 years, at risk of cardiovascular disease	4 weeks accelerometer + smartphone and web interfaces (+ smartphone-delivered text messages for additional group)	Blinded activity tracking
Suboc et al. [30] USA	114	Insufficiently active people 50–80 years	12 weeks pedometer + interactive website including peer forum	Usual practice
Thompson et al. [31] USA	49	Sedentary people ≥65 years	6 months accelerometer + bi-monthly face-to-face sessions + weekly telephone calls	Blinded activity tracking
Wijsman et al. [32] NL	235	Inactive people 60–70 years	12 weeks accelerometer + personal interactive website with e-coach	Waitlist (usual practice)

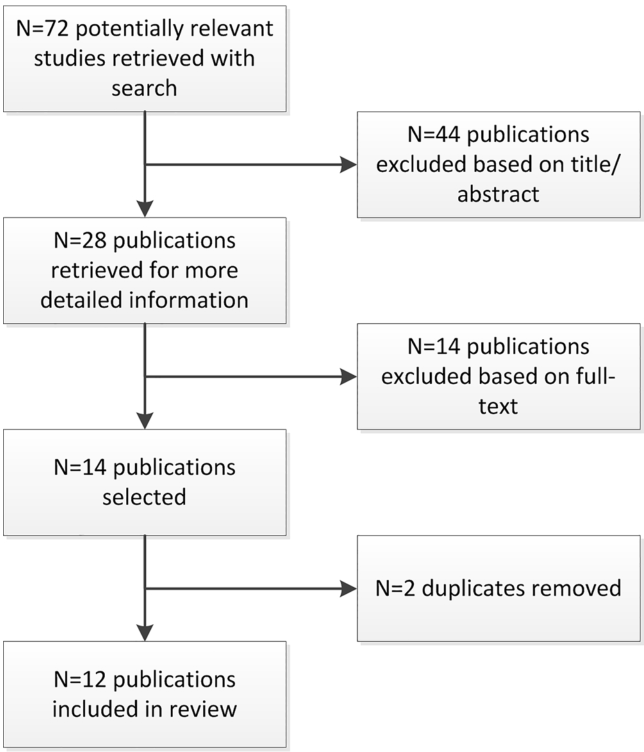

Fig. 1. Flowchart of study selection for the review.

participants the option to interact with a real coach via online e-consults, and Bickmore et al. [21] developed a virtual animated coach with whom participants could communicate through a structured interview online, following a predefined algorithm. Notably, all eHealth interventions that were included in this review did not only use a pedometer, uni-axial or tri-axial accelerometer as an objective assessment method to evaluate the effectiveness of the intervention (see Section 3.2 for details), but also used the wearable device as an integral component of the lifestyle intervention for self-monitoring.

Although most studies described a range of interactive techniques that were included in the eHealth interventions to change PA behaviour (e.g. goal-setting, self-monitoring, feedback), only five studies specifically referred to the theory underlying the design of their intervention components [25,26,28,29,32]. The CALO-RE framework on effective behaviour change techniques [33] was most frequently used [25,26,28]. The other two studies [29,32] used habit formation theory [34] and a combination of the stages of change model [35] and the I-change health behaviour change model [36]. A priori consideration of a theoretical framework is a crucial step in the development of a complex lifestyle intervention to ensure long-term uptake and understand its working mechanism [15]. The lack of using a theory in designing ICT-based interventions was also recognised in prior research [37] and underlines the need for addressing this in future studies. Particularly the behaviour change techniques in the CALO-RE framework described by Michie et al. [33] seem to be concrete techniques that can be readily incorporated in ICT solutions and have been associated with larger and sustained effects of lifestyle interventions [38].

Only five out of twelve studies collected data on user satisfaction and acceptability of the eHealth interventions in the older participants [21,24,25,28,29]. Tracking of how frequently participants actually used the eHealth interventions was only reported in four out of twelve studies [21,23,27,28]. The studies that reported user satisfaction indicated a high satisfaction with the eHealth intervention [21,24,25,28,29] as well as with wearing the wearable device [24,25,28,29]. Despite the diversity in intervention modalities, the eHealth components were well-received by the older adults participating in the studies. However, these results are based on a few studies and interventions were too heterogeneous to draw general conclusions. Studies evaluating eHealth interventions in older people should design

Table 2
Details on objective assessment of physical activity in included studies.

Study	Wearable device used	Attachment location	# days recorded	# days included in analysis	% compliance wearing guidelines (valid data)
Pedometer assessment					
Bickmore et al. [21]	Omron HJ-720ITC pedometer	At waist or pants pocket	30 days	Only if ≥7 days with valid data, > 5th percentile and ≤20,000 steps.	Intervention: 76% (2 mnth), 42% (12 mnth) Control: 76% (2 mnth), 56% (12 mnth)
Kim & Glanz [22]	Omron HJ-113 pedometer	Hip	NR	NR	NR
Kullgren et al. [23]	Fitbit pedometer	NR	7 days	NR	NR
Rowley et al. [24]	Omron HJ-720ITC pedometer	NR	NR	NR	Intervention 1:82% Intervention 2: 81% Control: 63%
Uni-axial accelerometer assessment					
Lewis et al. [25]	Sense Wear accelerometer	Wrist	7 days	Only if > 1 h per day	Intervention: 73.1/90 days Control: 71.4/90 days
Tri-axial accelerometer assessment					
Cadmus-Bertram et al. [26]	ActiGraph GT3X+ tri-axial accelerometer	Hip	7 days	NR	95% 7 valid days, 5% 5–6 valid days
Fukuoka et al. [27]	Omron HJA-350IT tri-axial accelerometer	Waist	7 days	Only if ≥4 days with ≥8 h per day	91.2% of study time
Lyons et al. [28]	ActivPAL tri-axial accelerometer	Front thigh, using tape	7 days	Only if > 5th percentile	NR
Martin et al. [29]	Fitbug Orb tri-axial accelerometer	NR	NR	NR	Intervention: 100% Control: 94%
Suboc et al. [30]	Omron HJ-720ITC pedometer & ActiGraph GTX3 accelerometer	NR	7 days	Only if ≥4 days with valid data	Intervention 1: 89% Intervention 2: 97% Control: 85%
Thompson et al. [31]	MSR Eletronics GmbH tri-axial accelerometer	Waist, at back, using elastic band	14 days	NR	NR
Wijsman et al. [32]	GENEActiv tri-axial accelerometer	Ankle and wrist, right side	7 days	Only if ≥5 days with valid data	Intervention: 90% (ankle), 91% (wrist) Control: 94% (ankle), 91% (wrist)

NR = not reported.

a process evaluation alongside the effectiveness evaluation to provide a better understanding of the acceptability and actual uptake of ICT-based interventions in these older populations [39].

3.2. Objective assessment of physical activity

Five studies used pedometers [21–24] or a uni-axial accelerometer [25] to assess PA in daily life, whereas the other seven used tri-axial accelerometers [26–32] (Table 2). The latter are preferred since they are more accurate in capturing light PA compared to pedometers and uni-axial accelerometers [19].

The methodology for objectively measuring PA in daily life is still under development and there is no consensus on when to measure, which fixation locations to use, and how to analyse the acquired data [18]. This is reflected in the different measurement protocols reported by the studies. The location used for attaching the wearable device ranged from ankle [32], waist [21,27,31], hip [22,26], to front of the thigh [28,32] and is likely due to the specific wearable devices used in the study.

Most studies recorded seven days to obtain daily PA estimates [23,25–28,30,32], but some extended this to 14 [31] or 30 days [21] to evaluate the effectiveness of the intervention. Presently, there is no consensus on the minimum time of recording needed for a reliable assessment of PA with accelerometers [18], yet a minimum of two days with valid data (which they defined as > 75% wear-time) has been recommended to reliably estimate PA outcomes at a group level, and a minimum of four days to reliably estimate PA in individuals [40]. Four studies reported protocols that are in line with these recommendations [21,27,30,32].

Two studies did not apply a protocol that ensured a minimum number of days with valid data for estimating daily PA (i.e. those studies used data only if the wearable device was worn > 1 h per da y[25] and only if recorded data was > 5th percentile of all collected data [28]). Six studies did not provide any details on requirements of quality of the data derived from the pedometers or accelerometers for the analysis [22–24,26,29,31]. Compliance with wearing the wearable devices was overall high, ranging from 75% [24] to 97% [29]. This was also the case in the four studies that are in line with the recommendation, with wearing compliance ranging from 76% [21] to 92% [32]. However, in the only study that assessed PA at 12 months follow-up, wearing compliance dropped from 76% at two months to 49% at twelve months [21]. Based on these studies, it seems feasible to use wearable devices for measuring PA in daily life in older populations at the short term, but procedures for data collection require standardisation and researchers should consider data quality assurance when deriving PA outcomes from the data [40], particularly for (long term) effect evaluation.

3.3. Effectiveness interventions in terms of physical activity behaviour

All eHealth interventions described in this review shared a common aim: promoting PA behaviour and reducing sedentary behaviour in older people. With the wearable devices described above, the outcome measures that were reported in studies were the average daily step counts [21–24,26–32] and average daily minutes of PA behaviour in studies using accelerometers [25–30,32]. The time point at which effectiveness was evaluated was in nearly all studies immediately after the intervention period, ranging from 4 weeks [29] to 6 months [31]. Only Bickmore and colleagues evaluated long-term effectiveness at 12 months follow-up [21].

The effects reported by the eleven studies that evaluated step counts were quite diverse. Overall, five studies showed a significant increase in daily steps in the intervention group compared to the control group [21,22,24,27,30], while four studies did not demonstrate a significant increase [23,26,28,31] (Table 3). Two studies reported conflicting results. Martin and colleagues found a significant increase in step counts solely in the intervention group that received text messages on top of using an interactive website and not in the group that used only the interactive website [29]. In contrast, Wijsman and colleagues did not find a significant effect on PA assessed from an accelerometer worn at the wrist, while they did find a significant increase in PA from similar data obtained at the ankle [32]. The authors attributed this difference to the cycling habits of their Dutch population, which might be better detected by an ankle-worn device [32]. Furthermore, prior research showed that signals from wrist-worn devices might be more prone to noise (i.e. from different tasks done with the hands while active) and are hence less accurate in recognising whole body PA[41]. Nevertheless, these observations call for standardisation of wearing location and validation of employed activity recognition algorithms. The only study reporting long-term follow-up of 12 months showed initial increases in daily step count in the intervention group compared to the control group (adjusted mean intervention group = 4041 steps, control group = 3499 steps, $p = 0.01$) [21]. However, this effect faded out after 12 months of follow-up (adjusted mean intervention group = 3861 steps, control group = 3383 steps, $p = 0.09$) [21].

In six studies, participants in the control condition also received a pedometer that was not blinded and hence they could self-monitor their own PA [21–23,25–27] (Table 1). This might have resulted in an underestimation of the actual effect of the eHealth interventions in these studies, since one might argue that the feedback provided by the pedometer in itself already constitutes as ICT-based PA promotion. Indeed, the findings across these studies were inconsistent, with some studies finding significant increases in daily step count compared to the control group [21,22,27], while others did not [23,26].

Seven studies reported results for daily minutes spent in PA behaviour [25–30,32]. The types of PA that were considered differed considerably across studies (Table 3); three studies reported results for different intensities of PA behaviour (i.e. light, moderate, vigorous) [26,27,30], three studies reported results for moderate to vigorous PA (MVPA) [25,26,32], one study distinguished between time spent on total PA behaviour vs. aerobic PA [29] and one study distinguished between sitting and stepping behaviour [28]. It is important to realise that the reported studies used different guidelines for cut-off points to label the intensity of the PA (i.e. light, moderate, vigorous) [42–44]. Although the guidelines only differ slightly in metabolic equivalent of task (MET) values for the cut-offs, this hampers a straightforward comparison between studies. Table 3 shows that findings were heterogeneous across studies. The results from the studies that looked at different intensities of PA suggest that eHealth interventions are mostly effective in promoting activities of moderate intensity [27,28,30]. Yet, standardisation of cut-off points for labelling intensity of PA is needed before a more definite conclusion can be drawn.

When interpreting the abovementioned results, it is important to realise that the PA outcomes evaluated in the studies were on the level of counting the total amount of PA (either in steps or in minutes). Data from accelerometers can also provide useful insights into activity patterns over the day [45], transitions between different types of PA and complexity of the PA behaviour [46]. These more detailed outcomes are not yet considered in the trials discussed in this review, but may yield new insights in the effects of lifestyle interventions for older people in the future.

A straightforward comparison of the effectiveness of the different eHealth interventions in this overview is complicated, as the intervention components and outcome measures differed considerably across studies [47]. The fact that many of the studies were not powered to find a significant treatment effect [22,25–28,31] further complicates this. The current evidence seems to point to a small but positive effect of promoting PA right after administering the intervention, that might be explained by an increase in moderate PA. Still, evidence for the highly desired long-term effects of eHealth interventions for increasing PA in older adults is currently lacking and larger studies with longer follow-up are needed to provide this evidence.

Table 3
eHealth intervention effects on objectively measured physical activity in included studies.

Study	Time point	Outcome daily step count: Effect size	Direction effect	Outcome daily minutes of physical activity: Type physical activity	Effect size	Direction effect
Pedometer assessment						
Bickmore et al. [21]	2 months	Adjusted mean T_1 I = 4041 steps, C = 3499 steps, $p = 0.01$.	+			
	12 months	Adjusted mean T_2 I = 3,861steps, C = 3383 steps, $p = 0.09$.	0			
Kim & Glanz [22]	6 weeks	T_0: I = 5852 ± 1961 steps, C = 4382 ± 2085 steps. T_1: I = 6531 ± 2648 steps, C = 4780 ± 1978 steps, group*time $p < 0.05$.	+			
Kullgren et al. [23]	16 weeks	Mean change I peer website = 833 [1256; 2922] steps; I peer website + lottery = 1178 [1081; 3437] steps, C = 1247 [411; 2082] steps. Comparison I peer website vs. C, $p = 0.51$; I peer website + lottery vs. C, $p = 0.93$.	0			
Rowley et al. [24]	12 weeks	T_0: I PM + website = 4688 ± 1475 steps, I PM only = 4853 ± 1455 steps, C = 4690 ± 1475 steps. T_1: I PM + website = 10,268 ± 3022 steps, I PM only = 7869 ± 2118 steps, C = 4654 ± 1447 steps, group*time $p < 0.001$.	+			
Uni-axial accelerometer assessment						
Lewis et al. [25]	12 weeks			MVPA	Mean change I = 11.1 ± NR min, C = 0.2 ± NR min, $p = 0.29$.	0
Tri-axial accelerometer assessment						
Cadmus-Bertram et al. [26]	16 weeks	Mean change I = 789 ± 1979 steps, C = 362 ± 1605 steps, $p = 0.30$.	0	Light PA	Mean change I = −14 ± 204 min, C = −33 ± 225 min, $p = 0.54$.	0
				MVPA	Mean change I = 62 ± 108 min, C = −13 ± 89 min, $p = 0.11$.	0
Fukuoka et al. [27]	20 weeks	Mean change I = 2551 ± 4,712steps, C = −734 ± 3308 steps, $p < 0.001$.	+	Light PA	Mean change I = 17 ± 167 min, C = −49 ± 151 min, $p = 0.05$.	0
				Moderate PA	Mean change I = 16 ± 46 min, C = −4.2 ± 29 min, $p < 0.001$.	+
				Vigorous PA	Mean change I = 2.30 ± 11.0 min, C = −0.36 ± 5.1 min, $p = 0.11$.	+
Lyons et al. [28]	12 weeks	I vs. C, effect size d = 0.26 [−0.07; 0.59].	0	Sitting time	I vs. C, effect size d = −0.21 [−0.54; 0.12].	0
				Stepping time	I vs. C, effect size d = 0.35 [0.02; 0.68].	+
Martin et al. [29]	4 weeks	I AM + website + text messages vs. C, mean difference = 3376 [1951; 4801], $p < 0.001$.	0/+	Total PA	I AM + website + text messages vs. C, mean difference = 29 [13; 45], $p < 0.001$.	0/+
		I AM + website vs. C, mean difference = 842 [−564; 2248], $p = 0.23$.		Aerobic PA	I AM + website vs. C, mean difference = 8 [−7; 23], $p = 0.28$.	

(continued on next page)

Table 3 (*continued*)

Study	Time point	Outcome daily step count: Effect size	Outcome daily step count: Direction effect	Outcome daily minutes of physical activity: Type physical activity	Outcome daily minutes of physical activity: Effect size	Outcome daily minutes of physical activity: Direction effect
					I AM + website + text messages vs. C, mean difference = 16 [7; 23], $p < 0.001$. I AM + website vs. C, mean difference = 2 [−6; 8], $p = 0.71$.	0/+
Suboc et al. [30]	12 weeks	T_0: I PM + website = 5474 ± 1512 steps, I PM only = 5136 ± 1554 steps, C = 4931 ± 1667 steps. T_1: I PM + website = 8167 ± 3111 steps, I PM only = 9596 ± 3907 steps, C = 5410 ± 2410 steps, group*time $p < 0.001$.	+	Sedentary PA	T_0: I PM + website = 657 ± 90 min, I PM only = 659 ± 115 min, C = 654 ± 109 min. T_1: I PM + website = 641 ± 113 min, I PM only = 624 ± 120 min, C = 636 ± 109 min, group*time $p = 0.77$.	0
				Light PA	T_0: I PM + website = 266 ± 74 min, I PM only = 256 ± 62 min, C = 237 ± 62 min. T_1: I PM + website = 267 ± 74 min, I PM only = 257 ± 67 min, C = 234 ± 71 min, group*time $p = 0.94$.	0
				Moderate PA	T_0: I PM + website = 19 ± 14 min, I PM only = 19 ± 11 min, C = 16 ± 10 min. T_1: I PM + website = 35 ± 11 min, I PM only = 48 ± 31 min, C = 17 ± 14 min, group*time $p < 0.001$.	+
				Vigorous PA	T_0: I PM + website = 1 ± 2 min, I PM only = 0 ± 2 min, C = 1 ± 5 min. T_1: I PM + website = 1 ± 4 min, I PM only = 1 ± 3 min, C = 0 ± 1 min, group*time $p = 0.22$.	0

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Table 3 (*continued*)

Study	Time point	Outcome daily step count: Effect size	Outcome daily step count: Direction effect	Outcome daily minutes of physical activity: Type physical activity	Outcome daily minutes of physical activity: Effect size	Outcome daily minutes of physical activity: Direction effect
Thompson et al. [31]	6 months	Mean change I = −218 ± 1032 steps, C = −584 ± 940 steps; p = 0.21.	0			
Wijsman et al. [32]	12 weeks	% increase (ankle-worn measurement) intervention = 46% ± 7%, C = 12% ± 3%, p < 0.001. % increase (wrist-worn measurement) intervention = 11% ± 3%, C = 5% ± 2%, p = 0.11.–>	0/+	MVPA	Mean change I = 11 ± 2.1 min, C = −0.1 ± 1.5 min, p = 0.001.	+

Values reported are means ± standard deviation or means [95% confidence interval].
+ = objective physical activity increased in intervention group; 0 = no statistically significant effect; AM = accelerometer; C = control; I = intervention; MVPA = moderate to vigorous physical activity; NR = not reported; PA = physical activity; PM = pedometer; T_0 = baseline assessment; T_1 = follow-up assessment; T_2 = second follow-up assessment.

4. Conclusions

This overview shows that eHealth interventions for promoting an active lifestyle, delivered in a wide variety of modalities, appear to be acceptable for older populations and have positive effects on increasing PA in the short-term. However, caution is warranted since many studies were underpowered and long-term effects have not yet been established. Larger studies with theory-based interventions and a longer follow-up are needed to fully understand the potential and effective components of eHealth interventions for promoting and sustaining an active lifestyle in older people. The objective assessment of PA through pedometers or accelerometers was used in all studies as part of the intervention for self-monitoring of PA levels, with high compliance by the older participants. Standardised protocols on collecting and analysing PA data from wearable devices are needed to better compare findings. Future research should also consider activity patterns, in addition to the amount of PA, to provide a more comprehensive measurement of PA behaviour in daily life.

Contributors

All authors were involved in the study design.

Nini H Jonkman performed the data collection and analysis, and drafted the manuscript.

Kimberley S van Schooten, Andrea B Maier and Mirjam Pijnappels provided input with the interpretation of the data, and contributed to critical revision of the manuscript.

All authors approved the final version of the manuscript.

Nini H Jonkman had full access to all data and had final responsibility for the decision to submit for publication.

Nini H Jonkman, Andrea B Maier and Mirjam Pijnappels are the guarantors of this article.

Conflict of interest

The authors declare that they have no conflict of interest.

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Provenance and peer review

This article has undergone peer review.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.maturitas.2018.04.010.

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