

Using feedback through digital technology to disrupt and change habitual behavior: A critical review of current literature

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Abstract

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Habitual behavior is often hard to change because of a lack of self-monitoring skills.

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Digital technologies offer an unprecedented chance to facilitate self-monitoring by delivering

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feedback on undesired habitual behavior. This review analyzed the results of 72 studies in which

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feedback from digital technology attempted to disrupt and change undesired habits. A vast

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majority of these studies found that feedback through digital technology is an effective way to

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disrupt habits, regardless of target behavior or feedback technology used.

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Unfortunately, methodological issues limit our confidence in the findings of all but 14 of

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the 50 studies with quantitative measurements in this review. Furthermore, only 4 studies tested

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for (and only 3 of those 4 found) sustained habit change, and it remains unclear how feedback

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from digital technology is moderated by receiver states and traits, as well as feedback

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characteristics such as feedback sign, comparison, tailoring, modality, frequency, timing and

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duration. We conclude with recommendations for new research directions.

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Keywords

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Digital technology; mobile and interactive technology; feedback; behavior change; habit

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change; habit disruption

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Using Feedback from Digital Technology
to Disrupt and Change Habitual Behavior:
A Critical Review of Current Literature

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1. Introduction

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A variety of digital solutions to help us change detrimental or outdated habitual behavior have arrived on the market. These so-called *quantified self*-solutions, also known as *persuasive technologies*, aim to alter ingrained habits by presenting people with behavioral feedback through mobile and interactive devices and applications. These technologies can help individuals improve their health and the environment by increasing awareness and improving the self-regulation of behavior, something that does not come easily to us. Opportunities to incorporate such technologies in daily life have risen dramatically in recent years. In many nations, a great share of the general populace owns a smartphone or other kind of smart device and seems willing to use technology to change unwanted behaviors. For instance, more than 69% of US citizens track at least one health behavior, with 14% using a specialized tracker (Fox & Duggan, 2012). Manufacturers are jumping on this bandwagon, offering new ways to measure behavior, e.g. through Apple's Research Kit (Moynihan, 2015).

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Few of these quantified self-products have been tested in controlled circumstances (Cowan, Bowers, Beale, & Pinder, 2013). Moreover, most solutions lack scientific evidence, with positive anecdotal reports from practice comprising the basis of our understanding (Cowan et al., 2013; Schoffman, Turner-McGrievy, Jones, & Wilcox, 2013). As yet, the potential of

42 digital technology to disrupt and possibly even change habits through feedback on habitual
43 behaviors remains unclear.

44 This paper addresses this gap in the literature by presenting a review of existing studies
45 on the use of feedback generated by digital technology to disrupt and change automatic, habitual
46 behaviors. This review adds to the current debate by providing an overview of existing evidence,
47 accentuating and addressing gaps in current knowledge and laying an evidentiary foundation for
48 digital technology solutions aimed at habit change.

49 To do so, we first assess the drawbacks of habitual behavior and the strategies that may
50 be applied to disrupt undesired habits. Second, we then discuss the role of self-monitoring in
51 habit disruption and the role feedback from external sources can play in self-monitoring. In the
52 third section, we look at known influences of feedback efficacy, and consider whether insights
53 into the effect of feedback on habitual behavior in general are valid when applied to feedback
54 delivered through digital technology. Finally, we review findings on the use of digital technology
55 that utilizes feedback and suggest avenues for future research.

56

57 **1.1 Habitual behavior**

58 In everyday life, habits, commonly defined as "behavior (...) prompted automatically by
59 situational cues, as a result of learned cue-behavior associations" (Wood & Neal, 2009, pp. 580;
60 Gardner, 2014, p.1), help us to come to terms with the enormous complexity of everyday life.
61 However, some of the biggest threats to personal and planetary wellbeing are direct
62 consequences of our habitual behavior. The cue-response-chain of a strong habit is a rigid
63 structure, which overrides contradictory behavioral intentions (Verplanken & Faes, 1999;
64 Verplanken & Wood, 2006). This may lead to undesired results when cue-response-pairs have a

65 satisfying short-term effect but lead to damaging consequences in the long run, as with snacking
66 or alcohol abuse. Furthermore, since habits do not take into account current context, changed
67 circumstances may render habits unproductive for contemporary life, even though the behavior
68 may have led to rewards in the past.

69 Because habitual behavior circumvents active consideration of the current context, it is
70 hard to change habits using interventions aimed at controlled processing, e.g. through persuasive
71 messages (Verplanken & Wood, 2006; Jager 2003). One powerful strategy to disrupt habits is
72 therefore to change the circumstances so that habit cueing does not occur (Verplanken & Wood,
73 2006) or to alter the external cues that lead to habit execution (e.g. in Aarts & Dijksterhuis,
74 2003). However, these strategies have practical difficulties, since manipulating or avoiding cues
75 is often impossible (Quinn, Pascoe, Wood, & Neal, 2010) and not always seen as ethical,
76 because receivers may not always consciously notice the manipulations, which places their
77 consequences outside the reach of conscious scrutiny (Verbeek, 2006).

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79 **1.2 Disrupting and changing habitual behavior by self-monitoring and feedback**

80 The automaticity of habitual behavior means that execution is often at least partially
81 unconscious and may start without conscious intent (Bargh, 1994). Therefore, one way to disrupt
82 undesired habits is to bring habitual behavior and its context to (conscious) awareness. Self-
83 monitoring, the procedure by which individuals record the occurrences of their own target
84 behaviors (Nelson & Hayes, 1981), enables perception of our own behavior and adaption to the
85 current context. Thus, self-monitoring leads to decreases in unwanted behavior (Quinn et al.,
86 2010).

87 Unfortunately, self-monitoring is difficult for even the most motivated individual
88 (Wilson, 2002). For example, there is often a discrepancy between self-reported and actual
89 performance, as shown in diverse behaviors such as calorie intake (Lichtman et al., 1992),
90 weight and BMI - especially in overweight participants (Pursey, Burrows, Stanwell, and Collins,
91 2014), the amount of exercise (Lichtman et al., 1992), actual versus perceived water use
92 (Hamilton, 1985; Millock & Nauges, 2010), and even the reporting of relatively stable personal
93 data such as height (Pursey et al., 2014).

94 Accurate self-monitoring is greatly improved by personalized information from external
95 sources (Kim et al., 2013; Li, Dey, & Forlizzi, 2010). The intentional delivery of such
96 information about performance or behavior (or about the impact of one's performance or
97 behavior) in order to facilitate behavior change is commonly referred to as *feedback* (Van
98 Velsor, Leslie, & Fleenor, 1997, p. 36). In this review, we adopt the definition of feedback
99 offered by Kluger and Denisi (1996), seeing feedback as "actions taken by (an) external agent(s)
100 to provide information regarding some aspect(s) of one's task performance"¹.

101 The beneficial effect of feedback on performance has been established in a range of
102 fields. In education, the role of feedback is especially well established. Hattie and Timperley
103 (2007) performed a synthesis of meta-analyses of feedback in educational contexts and reported
104 an average effect size of 0.79 for feedback interventions, almost twice the average effect size of
105 general educational interventions (0.40). This implies that feedback interventions in general are
106 not only capable of disrupting undesirable habits, but can also play a significant role in changing
107 those behaviors. Similarly, feedback has been shown to be effective in an increasing range of

¹ This definition excludes non-task-related feedback ("he just does not like you"), and intrinsic, task-generated feedback (e.g. getting coffee from a machine and seeing that your coffee cup is full), whilst including feedback on *how* a task is performed (e.g. "you kicked the ball with the tips of your toes; you should have used the instep" in football training).

108 controlled studies regarding both health (Gardner et al., 2010) and sustainability (Darby, 2006;
109 Froehlich, Findlater, & Landay, 2010; Fischer, 2008).

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111 **1.3 Feedback on behavior through digital technology**

112 Direct, instant feedback used to be difficult to deliver regularly on a large scale. The
113 delivery of feedback was restricted to either distant, impersonal media such as utility bills and
114 letters, or cost-intensive face-to-face communication with trained personnel. The advent of
115 mobile and interactive media has changed that. In recent years, technological developments have
116 enabled a surge of behavior-changing interventions. A range of mobile apps, wearable devices,
117 web-based platforms and in-home displays give us feedback on our behavior and monitor
118 behavior that previously remained hidden. There are apps and wristbands to support us in
119 physical exercise, applications for weight loss, in-home displays to encourage us to use less
120 energy, etcetera.

121 Already, more than half of smartphone users gather health-related data with their phone,
122 one in five has installed at least one health-behavior related app (Fox & Duggan, 2012) and one
123 in ten Americans owns some sort of automatic activity tracker (Ledger & McCaffrey, 2014).
124 Similarly, many European countries aim to achieve smart energy meter installation in every
125 home by 2020 (Faruqui, Harris, & Hledik, 2010).

126 Digital technology can offer constant, real-time updates on our progress, powered by
127 sensitive measuring devices, often worn on the body. The widespread use of sensing systems
128 means that automatically generated data about the undesired behaviors can be made available,
129 without the need for possibly problematic self-reporting. Monitoring devices can be used for a
130 range of data-gathering causes including health statistics like heart rate, blood pressure, and

131 blood sugar (Verplanken & Wood, 2006) and environmentally important data on energy use
132 (Verplanken & Wood, 2006; Froehlich, Findlater, & Landay, 2010).

133 Besides data generation, digital technology can offer habit-disrupting cues such as light
134 signals, buzzes, beeps, and push messages. Digital technology is not only useful to present users
135 with evaluations of past behavior ("reflection-on-action"); because of the ubiquity of mobile and
136 handheld devices, digital technology offers an unprecedented opportunity for "reflection-in-
137 action" (Schön, 1984), the analysis of behavior as it occurs.

138 The availability of interactive displays provides ample opportunity for new types of
139 feedback. A power socket may be enhanced to report energy use (Heller & Borchers, 2011), a
140 shower head can give us feedback on water use or shower time (Andler, Woolf, & Wilson,
141 2013), or a power cable can move around as if in agony if connected devices are left in stand-by
142 mode (Laschke, Hassenzahl, & Dieffenbach, 2011).

143 Digital technology has a number of distinct advantages over human persuaders. Devices
144 can be (irritatingly) persistent, guarantee greater anonymity and have access to areas where
145 people are not welcome (e.g. the bedroom or bathroom) or unable to go (e.g. inside clothing or
146 household appliances). Moreover, digital technology is relatively easy to replicate, distribute and
147 tailor to specific needs (Fogg, 2003). However, there are some disadvantages: digital technology
148 is a lot easier to ignore or shut down than messages delivered by human persuaders.
149 Furthermore, digital technology solutions are easily forgotten, lost or otherwise misplaced. For
150 example, over half of those that have owned a wearable fitness tracker no longer use it, and a
151 third of the users quits use in the first six months after purchase (Ledger & McCaffrey, 2014).
152 Yet, in providing automatically delivered feedback for habit change, the benefits of digital
153 technology may very well outweigh the disadvantages.

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155 **1.4 How feedback works: Mechanisms underlying feedback efficacy**

156 Control theory provides insight into the mechanisms underlying the effect of feedback
157 (Carver & Scheier, 1985). According to control theory, reflective behavior change processes are
158 reminiscent of a thermostat. When looking to change their behavior, people compare their
159 performance to a behavioral goal. When a discrepancy is noted, given enough motivation,
160 opportunity, and the right abilities, people will attempt to reduce this discrepancy. The efficacy
161 of this regulatory cycle is moderated by three executive function skills (cf. Hoffman,
162 Schmeichel, & Baddeley, 2012): keeping a goal salient in working memory or bringing the goal
163 back to working memory when needed; the ability to inhibit undesired automatic responses; and
164 the ability to switch between tasks or mental sets.

165 Feedback supports reflection by increasing knowledge and awareness of behaviors and
166 their impacts. Many behaviors are of such automaticity, that their performance is at least partly
167 subconscious. Knowing *that* and *when* a habit occurs opens up possibilities for behavior change.
168 Feedback also enables us to compare the consequences of our behavior to our current goals and
169 adapt when the behavior does not fit the context. Furthermore, it also serves to increase general
170 self-awareness, which in turn increases our capabilities to inhibit undesired behaviors (Alberts,
171 Martijn & De Vries, 2011).

172 Feedback also has motivational consequences. We are driven by motivations to approach
173 experiences that are expected to be pleasurable, and avoid unpleasant experiences (Elliot &
174 Covington, 2001; Higgins, 1997). Both the negative emotions caused by an observed increasing
175 discrepancy between goals and performance, and the positive emotions caused by a decreasing
176 discrepancy, can increase our motivation to reach our goals (Carver & Scheier, 2011; Deci,

177 Koestner & Ryan, 1999). Furthermore, among competing behaviors, those supported by
178 feedback are given priority over those without feedback (Northcraft, Schmidt, & Ashford, 2011).

179 **1.5 Factors moderating feedback efficacy**

180 In a meta-analysis of 607 studies, Kluger and DeNisi (1996) found that, generally
181 speaking, two thirds of all feedback interventions increased performance. However, the
182 remaining third of the interventions had an opposite, detrimental effect on performance.
183 Importantly, this means that even though we can expect a habit-disrupting effect from well-
184 designed feedback interventions, this does not automatically signify that the feedback
185 intervention will lead to change in the desired direction.

186 Furthermore this suggests that an interplay of receiver states and traits on the one hand,
187 and feedback properties such as content (e.g. sign, comparison and level of detail), timing,
188 modality, frequency, duration, and presentation on the other, influence feedback effectiveness
189 (Fischer, 2008). The moderating effects of both receiver traits and states and feedback properties
190 will be discussed below.

191 ***1.5.1 Interpersonal and intra-personal differences***

192 Feedback efficacy is moderated by all kinds of characteristics of the feedback receiver, in
193 an interplay of stable and more dynamic factors. A great deal of the expected moderators is
194 stable and relatively uncontrollable, such as socio-economic status (e.g., Maitland, Chambers &
195 Siek, 2009: affluent participants seem to benefit more from feedback interventions than poorer
196 participants) and gender (e.g. Guadagno & Cialdini, 2007; Ho et al., 2013).

197 In any self-control mechanism, executive control capabilities play an important role, such
198 as the capacity for self-regulation. Differences in personality and context determine the degree to
199 which an individual is capable of exercising such control (Baumeister & Heatherton, 1996;

200 Braverman, 2008; Kuhl, 1985). In addition, self-regulating capacity is in finite supply
201 (Baumeister et al., 1998).

202 Feedback efficacy is also influenced by relatively fleeting states such as high initial
203 engagement with the target goal, strong motivation or a high perceived self-efficacy (Bandura,
204 1997). Self-regulation processes are cyclical in nature (Bandura, 1997; Zimmerman, 1998). This
205 indicates that high initial motivation leads to a greater feedback effect, which in turn leads to
206 increased motivation (e.g., Geister, Konradt, & Hertel, 2006). Similar cyclical effects can be
207 found for self-regulatory skills and perceived self-efficacy (e.g. Donovan & Hafsteinsson, 2006;
208 Multon, Brown & Lent, 1991).

209 To date, there is little or no evidence on whether these intra- and interpersonal factors that
210 are generally known to influence feedback efficacy, such as motivation and perceived self-
211 efficacy towards the goal, self-regulatory capabilities, and demographic and socio-economic
212 factors, have different effects on the efficacy of feedback when it is delivered through digital
213 technology. Since the latter is generally delivered in an individual context and not within the
214 social setting of interpersonal feedback, the effect of feedback through digital technology might
215 rely on capabilities and motivation of the receiver more than with interpersonal feedback.

216 ***1.5.2 Feedback properties***

217 Paying attention to carefully crafting the timing, delivery, and content of the feedback
218 can enhance the effectiveness of feedback interventions. In an extensive review of feedback on
219 household energy use, Fischer (2008) indicates that high frequency feedback delivered over a
220 long period by computerized and interactive tools provides an advantage in feedback
221 effectiveness. There are a number of feedback properties that may affect effectiveness, including
222 *technology, content, timing, modality, duration, frequency, and presentation and user*

223 *experience*. Generally, the largest effects can be expected from detailed, positively framed,
224 concurrent feedback ('reflection-in-action'), delivered continuously or on-demand through more
225 than one modality, during a long period.

226 ***Technology.*** Feedback can be delivered through many different technological channels,
227 ranging from websites and smartphone apps to wearables and in-home displays. The possibility
228 to deliver well-designed and automatically tailored, in-action, frequently delivered feedback over
229 a long period of time is one of the perceived strengths of digital, interactive technology. Because
230 behavior often is measured directly, a direct response is possible, and the all-pervasive use of
231 smartphones and other technologies means instant delivery on a large scale is relatively easy.

232 Each form of the technology has its advantages and disadvantages as a source of
233 feedback. For example SMS text messages, a well-researched and generally considered effective
234 means of feedback delivery (Hall, Cole-Lewis, & Bernhardt, 2015), are difficult to deliver at the
235 very moment the behavior occurs because of time lag. This delay can severely disrupt
236 performance, which may in some cases have negative consequences on behavioral fluency
237 (Bittner & Zondervan, 2015). Furthermore, text messages can only deliver content of limited
238 length (usually about 160 characters). On the other end of the spectrum, wearable activity
239 trackers can do real time tracking of behavioral data, and are capable of on-demand or
240 continuous delivery over a range of sensory channels without limits to the richness of the data
241 (Yang & Hsu, 2010).

242 ***Content.*** Tailoring content to fit receiver characteristics can be expected to affect
243 feedback effectiveness. Ample evidence from the literature shows that tailoring message content
244 to meet recipient motivation, traits, abilities and preferences increases the effectiveness of such
245 messages (e.g. Noar, Benac, & Harris, 2007; Noar, Harrington, Van Stee, & Aldrich, 2011; Ivers

246 et al., 2012; Kaptein, De Ruyter, Markopoulos, & Aarts, 2012). Such tailoring may encompass
247 utilizing negative, positive or neutral feedback (i.e. feedback sign); offering social, historical or
248 normative comparisons (or no comparison at all); and increasing or decreasing level of detail.

249 **Timing.** There has been substantial research on the effect of feedback timing on learning
250 (Hattie & Timperley, 2007, p. 98). Specifically, reflection-in-action can be expected to be more
251 effective than reflection-on-action. For instance, in electricity use, direct, short delay feedback on
252 energy usage generally leads to a 5–15% reduction in consumption, and indirect, long delay
253 feedback leads to a reduction of 0–10% (Darby, 2006).

254 **Modality.** Selecting optimal delivery through visual, auditive, or tactile channels, or a
255 combination of channels, increases feedback effectiveness (Hoggan, Crossan, Brewster, &
256 Kaaresoja, 2009; Warnock, McGee-Lennon, & Brewster, 2011; Braverman, 2008). An optimal
257 modality choice depends on the possibility of disruption and the need for detail. The visual mode
258 is more disruptive than the auditory, which is in turn more disruptive than tactile feedback.
259 Similarly, visual feedback can contain more detailed information than auditory, which in turn has
260 more capacity for detail than tactile feedback.

261 **Frequency and duration.** Frequency and duration of the feedback intervention also
262 influence feedback effectiveness. In general, the more frequent the feedback is delivered, over a
263 longer period of time, the more the intervention will contribute to behavior change. The benefits
264 of more frequent feedback are limited by cognitive capacity: as long as the frequency of the
265 feedback does not overwhelm an individual's cognitive resources, more feedback is better (Lam
266 et al., 2011). Current technological developments, especially those that concern use of mobile
267 and interactive platforms, make it possible to circumvent these limitations and easily deliver

268 much more frequent or even continuous feedback, with infinite durations. In theory, this should
269 increase feedback effectiveness.

270 ***Presentation and user experience.*** Research in web design (Tuch et al., 2012),
271 typography (Larson & Picard, 2005) and usability (Tractinsky, Katz, & Ikar, 2000) suggests that
272 visual design aspects and aesthetics determine the attitude towards a design as well as the
273 perceived ease of use (but not actual use). Consequently, users will feel more beneficial towards
274 an aesthetically pleasing intervention and will be more inclined to persevere in using it.
275 Moreover, a clear design might aid in emphasizing important information, personalizing the
276 feedback and improving the fluency of feedback. However, the design and presentation of the
277 feedback and technology must also fit participants' goals. For example, research on the design of
278 glucometers suggests that the desired look and feel depends on context; users favor a more
279 “medical” appearance when passing through customs on transatlantic flights and inconspicuous
280 or sporty looks in day to day life (O’Kane, Rogers, & Blandford, 2015).

281

282 **1.6 Reviewing the effects of feedback delivered by digital technology**

283 Feedback through digital, interactive technology can have two beneficial effects on
284 habitual behavior. Firstly, it can disrupt the automatic execution of the habitual behavior, making
285 it available for conscious scrutiny. Secondly, feedback can lead to durable behavior change.
286 Given the extensive evidence for the beneficial effect of feedback on habitual behavior change in
287 general (e.g. Brug et al., 1998; Fischer, 2008; Hattie & Timperley, 2007; Ivers et al, 2012,
288 Kluger & DeNisi, 1996), and the aforementioned benefits of digital technology over more
289 traditional forms of feedback delivery, one assumption in this work is that feedback delivered by
290 digital technology is at least as effective as 'regular' feedback in disrupting undesired habits.

313 from ACM/DL and 233 results from IEEE/Xplore; these results included peer-reviewed journal
314 papers as well as conference proceedings.

315 Abstracts from both result sets were checked for relevance. From these, 101 publications
316 with relevant and ambiguous abstracts were retained. Papers cited in included articles were
317 checked for eligibility. Ancestry searches were performed on the included articles through
318 Google Scholar, to retrieve more recent articles building upon the original work. From these
319 searches, a further 35 primary publications were included. This resulted in a set of 136 primary
320 sources.

321 From this set, 69 original papers matched the following inclusion criteria:

- 322 • The research has the primary purpose of changing habitual behavior, either increasing or
323 decreasing the behavior or stopping the behavior altogether. Habit is operationalized as
324 recurring behaviors with some degree of automaticity (Wood & Neal, 2009)
- 325 • Digital technology has to be used as the primary means of achieving behavior change
- 326 • The digital technology must use a tailored feedback mechanism delivered by (an) external
327 agent(s) to provide information regarding task performance
- 328 • The research must encompass some form of analysis of the effect of the intervention on the
329 targeted behavior, be it qualitative or quantitative.
- 330 • Because of rapid developments in the field of digital technology, only papers from the last
331 decade (2004 and later) were included.

332 All analyzed papers are included in the reference list and marked with an asterisk (*).

333 One included paper reported three relevant studies (Nakajima & Lehdonvirta, 2013) and two
334 papers reported two relevant studies (Connelly et al., 2006, and Stienstra, Wensveen, & Kuenen,
335 2011), all of which were separately scored. This resulted in a final set of 72 studies.

336 The broad range of dependent variables, feedback intervention technologies, and research
 337 methods applied in the included papers made it impossible to conduct a meta-analysis of results
 338 in such a way that it would produce reliable and valid insights (Borenstein, Hedges, Higgins, &
 339 Rothstein, 2009; Quintana, 2015). Consequently, a systematic review with a descriptive analysis
 340 (Garg, Hackam, & Tonelli, 2008) of the literature was performed. Even though, when compared
 341 to a meta-analysis, a systematic literature review has more limited possibilities to derive general
 342 conclusions, this approach is able to shed light on the general direction of effects, as well as
 343 identify gaps in the literature (ibidem). Furthermore, conducting a systematic literature review
 344 enables us to incorporate results from qualitative studies, which would not be possible in a meta-
 345 analysis.

346 We thematically classified target behaviors of the intervention, feedback technology,
 347 feedback characteristics (content (feedback sign, comparison, and level of tailoring), timing,
 348 modality, frequency, duration, data source), and the availability of visual examples of the design
 349 and provided feedback. For each intervention, number of participants, independent and variables,
 350 analysis method, results, and possible methodological concerns were scored.

351 The included studies covered a range of dependent variables, varying from energy
 352 consumption to motor skills and physical activity. A list of the occurrence of each category of
 353 dependent variable is included in table 1. A full list of included studies, including target
 354 behaviors, feedback content, characteristics, dependent and independent variables and
 355 measurement methods is available as an online supplement.

356

357 Table 1: dependent variables

358	24	energy and water consumption
359	11	motor skills (speed skating, posture, violin playing, tooth brushing)
360	10	healthy eating and weight loss

361	9	physical activity
362	6	driving
363	3	general wellbeing
364	3	waste reduction
365	2	break taking and resuming work
366	9	other (social feedback, bookshelf ordering, IQ training, printing
367		behavior, medication adherence, overfilling water cookers, transport mode choice)

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3. RESULTS AND DISCUSSION

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3.1 Methodological issues

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In this section, we first discuss the consequences of the diverse methodological approaches, followed by an analysis of review results ordered by theme – general effects of feedback on disrupting and changing habitual behavior, the effect of receiver characteristics, and the effects of different feedback technologies and characteristics. Finally, we discuss a few insights that transpired from qualitative results that were not based on a pre-posed hypothesis.

The broadness of the range of studies included in this review is reflected in the different methodological approaches used. Of the 72 studies included in this review, three studies took place under controlled (laboratory) circumstances, 20 were field studies (7 of which were set up as a randomized controlled trial), and 49 studies tested a prototype or design. With regard to methods of analysis, 21 studies used qualitative analysis, mostly user experience studies describing interactions with designed prototypes. 50 studies utilized some form of quantified measurement and analysis, in 15 cases together with qualitative measures. In one paper, data gathering and analysis were described so poorly, that it remained unclear which research methodology was used.

386 Each form of research design and method of analysis has its own unique merits to the
387 generation of knowledge. However, in every research design, reliability and validity should be
388 well thought-through, to prevent experimental artifacts such as the Hawthorne effect – mere
389 observation enhancing performance (cf. McCarney et al., 2007) –, demand characteristics –
390 participants' interpretation of what is expected of them (Orne, 1962), or unforeseen events
391 influencing performance – such as seasonal influences on energy use that may eclipse the effect
392 of a feedback intervention. In general, quantitative studies that include (active) control groups,
393 pre- and post-test measures, and use a fitting statistical test with ample power (Maxwell &
394 Delaney, 2004, p. 56–59) are better suited for this. In qualitative study designs, a well-structured
395 data collection and analysis strategy is necessary to reduce the chance of cherry-picking
396 precisely those results that fit the hypothesis (Patton, 1990).

397 Most of the included quantitative studies did not meet these criteria. 33 of 50 quantitative
398 studies did not report a strategy of dealing with experimental artifacts such as demand
399 characteristics or unforeseen external moderators. Of the 50 quantitative studies, 30 studies were
400 analyzed using statistical testing, yet only 8 out of these 30 studies showed sufficient statistical
401 power for the sort of analysis performed. This is important, since low statistical power implies a
402 large chance of type I and II errors (Cohen, 1992). Furthermore, low statistical power combined
403 with a significant result dramatically increases the chance of an overestimation of intervention
404 effects (Gelman & Carlin, 2014). In total, only 14 out of 50 studies with some sort of quantitative
405 measurements had sufficient statistical power plus an experimental design that would prevent the
406 occurrence of the most common experimental artifacts.

407 The 21 qualitative studies included in this review were all of sufficient rigor to avoid
408 cherry picking in results. Most studies used a form of structured interviewing as data collection

409 method, and reported some sort of systematic appraisal of the results. No qualitative studies had
410 obvious methodological shortcomings.

411 We focus our analysis on those studies that meet all criteria mentioned above, both
412 utilizing qualitative and quantitative methods. Subsequently, we will mention descriptive results
413 from studies that did not meet all these criteria, with a corresponding caveat.

414

415 **3.2 The effect of feedback through digital technology on *disrupting* habitual** 416 **behavior**

417 The effect of feedback through digital technology on disrupting habitual behavior is
418 generally confirmed by our analysis. Of the 72 studies included in this analysis, 59 studies show
419 a beneficial effect of feedback on disrupting habitual behavior. 13 of 14 studies with well-set up
420 quantitative experimental designs and ample statistical power report significant results. 25
421 studies show a beneficial effect based on qualitative measurements, including observation
422 reports, interviews and other user experience measures. Furthermore, from the remaining 37
423 quantitative studies, 32 studies report descriptive data that point in the direction of hypothesis. Of
424 all studies that report a beneficial effect, five studies found this effect to be partial, i.e. not
425 occurring in every expected condition.

426 Thirteen of fourteen experimental studies prove the beneficial effect of feedback through
427 digital technology on a broad range of habitual behaviors. Feedback increased fruit consumption
428 (Bech-Larsen & Grønhøj, 2013), safer driving behavior (Donmez, Boyle, & Lee, 2008; Maltz &
429 Shinar, 2004), motor learning (Lieberman & Breazeal, 2007) and posture training (Epstein et al.,
430 2012), lowering eating rate (Ford et al., 2010), increasing physical activity (Hurling et al., 2008;
431 Schulz et al., 2014), weight loss (Pellegrini et al., 2012; Schulz et al., 2014), limiting computer

432 use (Van Dantzig, Geleijnse, & Van Halteren, 2013), shower use (Willis et al., 2010), and
433 electricity consumption (Jain, Taylor, & Peschiera, 2012; Wood & Newborough, 2003;
434 Vassileva, Odlare, Wallin, & Dahlquist, 2012).

435 One well-designed quantitative study reported a null effect. The lack of effect in this
436 study, in which participants could volunteer to join a home energy reduction intervention
437 (Alahmad et al, 2012), could be ascribed to a ceiling effect caused by participant self-selection,
438 such that only highly motivated participants that already performed many energy-saving
439 behaviors took part. This could prove a limitation of the efficacy of feedback interventions: when
440 participants are already performing the behavior in some way, there is a limit to habit change
441 coming from feedback.

442 Seven qualitative studies reported no effects or even a contrary effect of feedback on
443 behavior change. One study on waste disposal (Comber & Thieme, 2013) and a study on
444 electricity usage (Hargreaves et al., 2010) found that although no behavior change was
445 registered, knowledge about which behaviors were desirable and which less so did increase. In
446 two studies, participants did not understand the manipulation (Gyllensward, Gustafsson & Bång,
447 2012; Kim et al., 2008). One further study (Nakajima & Lehdonvirta, 2013) on utilizing
448 feedback to encourage a certain ordering of books on a bookshelf, led participants to play around
449 with the installation, with inverse effects. Inverse effects were also found in a study on taking
450 breaks at work, where participants used social activity feedback to avoid colleagues or to find
451 empty rooms for meetings (Kirkham et al., 2013). This, too, may be a limitation of feedback:
452 receivers may not perceive the feedback as a cue towards the target behavior. Studies by Katzeff
453 et al. (2012) on energy use in the office, and Strengers (2011) on energy and water consumption

454 show how feedback may not per se lead to behavior change, but may in the latter case also cause
 455 post-hoc rationalizations of the undesired behavior.

456 Finally, four quantitative studies found null results; however, all four studies (Cowan et
 457 al., 2013; Rodgers & Bartram, 2011; Pereira et al., 2012; Quintal, Pereira & Nunes, 2012)
 458 suffered from a lack of statistical power, so their null finding may very well be due to small
 459 sample sizes, since descriptive results in all studies do show a small positive effect of the
 460 reported interventions.

461 Where possible, we calculated effect sizes of quantified measurement methods for
 462 comparison (table 2). 28 studies either reported effect sizes or presented their data in such a way
 463 that effect sizes could be calculated. Even though the broad range of dependent and independent
 464 variables used in the reviewed studies make direct comparison in the form of a meta-analysis
 465 unfeasible, an overview of effect sizes listed could in theory serve as an indication of effect sizes
 466 to be expected in feedback interventions on habitual behavior.

467 Because of the methodological issues in the greater part of these studies, the reported
 468 effect sizes should be used with extreme caution. Low statistical power, especially, increases the
 469 chance of inflated effect sizes (Gelman & Carlin, 2014), which would give at least a partial
 470 explanation of the size of the effects found in many studies in this review.

471

472 Table 2: Effect sizes (reported or calculated)

<i>Study</i>	<i>Effect Size (Cohen's d)</i>	<i>Dependent variable</i>	<i>Partic ipants</i>	<i>Analysis t</i>	<i>Issues²</i>	<i>Field³</i>
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Hurling et al., 2008	3.022	physical exercise	70	Other		b
Hoggan et al., 2010	2.5201	IQ training	9	a	a	a
Stamopoulos et al., 2014	2.3528	buying domestic products	32	b	a	a
Chang et al., 2008	2.129	Brushing teeth in children	13	c	a, b	a
Spelmezan, 2012	1.9604	snowboarding skill	10	a	a, b, c	a
Bruns Alonso et al., 2014	1.6101	toothbrushing stroke length	21	a	a	a
Van Dantzig et al., 2013	1.188	sedetary behavior	86	a		a
Lee, 2014	1.05	medicine adherence	12	b	a	a
Brumby et al., 2011	1.0 (task priority x performance, no choice), and 2.77 (task priority x performance, choice)	Information processing while using car simulation	24	a	a,c	a
Oshima, 2013	0.953	weight loss	56	b	a	b
Wang et al., 2013	0.928	body massages, stretching in computer use	39	b	a	a
Bentley et al., 2013	0.887	self-understanding in health behavior, wellbeing	60	f, b	b	b
Tulusan et al., 2013	0.835	driving eco-friendly	50	b	a	a
Qian et al., 2011	0.603	walking pace	20	a	a	a
Maltz et al., 2004	0.556 (distance), 0.317 (modality)	keeping distance to car in front	120 / 15 ***	a		a
Pellegrini et al., 2012	0.5198 for body weight	weight loss	51	a		b
Liu, 2014	0.471	time not working, stress	30	a	a	a
Spring et al., 2013	0.43	weight loss	70	h	d	b
Donmez et al., 2008	0.4268	braking, accelerating, glancing in driving in simulator	48	a	c	b
Bech-larsen et al., 2012	0.381	fruit and vegetable consumption	256	a		b
Willis et al., 2010	0.332 length, 0.451 volume	water usage, shower length	49 *	b	a	a
Ford et al., 2010	0.293	eating behavior in obese children	106	a		b
Schulz et al., 2014	0.28 (t1, sequential) and 0.18 (t2, simultaneous)	health behavior	5055	a, d	d	b
Ahlamad et al., 2012	0.143	Home energy use	151	b	d	a

Kim et al., 2008	0.107	knowledge of peers' sleeping behavior	6	b	a, b	a
Quintal et al., 2012	0.052	electricity consumption	13 *	e	a, b	a

473

474 *1 – Analysis method: a = Analysis of Variance, b = T-test, c = Nonparametric tests (e.g. Wilcoxon Signed Ranks), d = (Pearson's) Chi*
 475 *squared test, e = Correlations and regression, f = Descriptives only, h = Other*

476 *2 – Problems: a = underpowered, b = no control condition, c = lacking conditions, d = other (such as self-report measures, self-*
 477 *selection, sample distribution issues)*

478 *3 – Field: a = design research, hci, engineering; b = health and psychology*

479 **: number of households included in study; ** number of classes included in study; *** experimental condition / control condition*

480

481 **3.3 The effect of feedback through digital technology on *lasting* habit change**

482 The durability of the hypothesized effect was tested in only four of the 72 studies, three
 483 of which found at least partial evidence of lasting effects. A combination of a standard
 484 behavioral weight loss protocol and feedback from digital technology led to lasting weight loss
 485 after half a year of use (Pellegrini et al., 2012); a range of lifestyle-oriented interventions based
 486 on feedback had effects that were discernable even after two years after the single point
 487 intervention (Schultz et al., 2011); and delivering feedback to reduce eating rate led to a lasting
 488 decrease in weight after a year of use, which was still discernable six months after intervention
 489 completion (Ford et al., 2010).

490 Contrarily, in a study of thirteen households that involved an in-home display of energy
 491 use, Quintal, Pereira and Nunes (2012) found no significant effects of display use on energy
 492 consumption even after a full year. However, this lack of findings may be due to a lack of control
 493 conditions and/or low statistical power, since descriptive data do point in the direction of a
 494 positive effect.

495 For behavior change to take effect, however, sustained use of the intervention is needed:
 496 intervention adherence is known to be significantly correlated with intervention success (Burke

497 et al, 2008). Only three papers looked into sustained use of the feedback technology. First, in a
498 qualitative study on the use of health mash-ups translating information from different feedback
499 sources into natural language, almost all participants used the intervention for the full 90 days of
500 the project (Bentley et al., 2013). Contrarily, in a weight loss intervention (Pellegrini et al.,
501 2012), 20% of participants stopped within 6 months; and Pereira, Quintal, Nunes, and Bergés
502 (2012) found that even though they could report initial success, after four weeks interest in their
503 feedback intervention on energy use was waning, with detrimental results on feedback effect.
504 These latter two findings are in line with literature on sustained use of behavior change
505 interventions, which show a sharp decline in self-monitoring willingness after 10-14 days (e.g.
506 Burke et al., 2008; Patrick et al., 2009) and a linear decline of the use of wearable technology
507 which results in about 40% dropout within 12 months (Ledger & McCaffrey, 2014).

508

509 **3.4 The effect of interpersonal and intrapersonal differences**

510 Previous research has shown that not everybody benefits equally from feedback
511 interventions. Both stable (traits) and dynamic (states) moderators are seen to influence feedback
512 efficacy. Surprisingly, only one study in this review looked directly at the effect of demographic
513 variables on feedback effectiveness. In an analysis of feedback on energy use in 2000
514 households, Vassileva et al. (2012) found that socio-economic factors such as income, age and
515 type of housing interacted with the preferred medium of feedback delivery. Unfortunately, their
516 work did not include the effect of socio-economic status on feedback effect.

517 In a similar vein, only a few papers took individual differences of any kind into account,
518 be it motivation, self-regulatory capabilities, or personality traits. Bech-Larsen & Grønhøj (2013)
519 found that people who consumed hardly any fruit benefited more from feedback than people who

520 already consumed close to the desired target, suggesting a ceiling effect to feedback
521 effectiveness that would cause underperformers to benefit more from feedback interventions than
522 high performers. Similarly, Tasic et al. (2012) found that people who used a lot of water for
523 showering decreased their water use a lot more than people who used less. Wallenborn et al.
524 (2011) found that men were more interested in the use of smart meters than women and indeed
525 used them more.

526 Finally, the null result in research reported by Alahmad et al. (2012) might be seen as a
527 further indication of ceiling effects in feedback interventions. If self-selection has a detrimental
528 effect on the effectiveness of a feedback intervention, it might be that this is because participants
529 are already performing the desired behavior to the maximum possible extent.

530 **3.5 The effect of feedback technology and properties**

531 Feedback content factors (such as feedback sign, level of tailoring, and comparison
532 level), the technology through which the feedback is delivered, feedback characteristics (such as
533 timing, modality, frequency and duration), and the presentation of the feedback, all may
534 influence the efficacy of feedback interventions. In this section, we first present results regarding
535 feedback content, followed by results regarding feedback technology, characteristics and design.

536 For each study, we analyzed the sign of the feedback, i.e. whether the digital technology
537 delivered positive feedback ("You have exceeded your goal by 1,000 steps"), negative feedback
538 ("you are still 1,000 steps short of your goal") or neutral feedback ("you have managed 9,000
539 steps today"). Furthermore, we analyzed the comparisons the digital technology made in
540 delivering the data, i.e. comparing to past performance, peer behavior, or abstract norms. Level
541 of tailoring was not taken into account, because every study in the review included some form of
542 tailoring.

543 **Feedback sign.** The vast majority of studies (55 out of 72) delivered feedback in such a
544 way that both positive and negative feedback were possible, 4 studies only utilized feedback with
545 a negative sign, and two studies only provided positive feedback. A further 12 studies provided
546 neutral feedback, i.e. without any form of reference to performance goals or norms and therefore
547 without sign. Two of these twelve studies combined neutral feedback for one dependent variable
548 with signed feedback for another dependent variable. In one study, the feedback was described
549 without detail, so no feedback sign could be established.

550 Only two studies directly compared positive and negative feedback. Both studies, which
551 compared the effect of rewards and penalties on engagement (Jain, Taylor, & Pescheira, 2012),
552 and the effect of positive with negative feedback on work pace interruptions (Liu & Pfaff, 2014),
553 found a greater effect for positive feedback than negative. Moreover, the latter study found that
554 negative feedback does indeed increase performance, but at the cost of a greater stress level.

555 **Feedback Comparison.** Different forms of comparisons can be made with feedback data.
556 Current performance can be compared to past performance (historic comparison), a social
557 comparison with peers or unknown counterparts can be delivered, or performance can be
558 compared to a norm or a goal (normative comparison). In this review, 52 studies made a
559 normative comparison in their feedback. 18 studies gave historic comparisons (8 of which
560 combining this with normative feedback, 1 with social feedback, and 2 with normative and social
561 feedback), 7 studies used social comparison (3 of which in combination with other forms of
562 comparisons). 7 studies delivered the data 'as is', without comparison. One study described the
563 feedback without detail, so no information about comparison could be extracted.

564 Two studies contrasted different kinds of comparisons directly. Jain, Taylor, and
565 Pescheira (2012) looked at the effect of normative and historic feedback comparisons in smart

566 energy meters, finding that historic comparisons resulted in greater effect, whereas normative
567 comparisons did not change energy use. In contrast, Sundramoorthy et al. (2011) found that
568 normative, social and historic comparisons resulted in greater energy saving.

569 All in all, on the basis of the data extracted in this review, it is not possible to ascribe a
570 more positive effect on feedback efficacy to a single strategy of comparison. This reflects
571 findings in literature on feedback in general.

572 ***Feedback technology.*** To deliver the feedback, 16 studies utilized a mobile phone app,
573 11 studies used an in-home display – mostly for energy use monitoring –, in 9 studies feedback
574 was delivered using a website, and 7 studies used a computer or tablet application. Four studies
575 provided participants with a wearable device capable of delivering vibrotactile feedback and
576 three studies used a driving simulator. SMS text messaging, Facebook apps, and interactive
577 public displays were used once. One study provided feedback both through a mobile phone app
578 and a website. The largest category is that of the 'smart' devices, used in 18 of the studies. These
579 devices often resemble generic household instruments, such as cutlery or scales, augmented with
580 sensors and actuators. All but three studies derived the data for the feedback directly from the
581 target behavior; three studies relied on self-report for the generation of feedback.

582 Each feedback technology has particular characteristics that impact the overall experience
583 of the user. The wearable vibrotactile devices could only deliver feedback in their own modality,
584 concurrent with behavior, and without possibilities for comparison to earlier results or
585 performance of others. SMS text messages could only be delivered retrospectively, as they rely
586 on technology with a time lag. However, technology choice was not associated with differences
587 in effects on habit disruption or change; positive results as well as null findings were spread

588 evenly across technologies. Unfortunately, none of the studies in the analysis directly compared
589 different technological channels.

590 **Feedback timing.** Of the reviewed studies, 20 delivered retrospective feedback, i.e.
591 feedback after the behavior had been performed. 52 studies delivered concurrent feedback, i.e.
592 during behavior performance. Two studies offered both forms for different behaviors, without a
593 direct comparison. One study (Donmez, Boyle, & Lee, 2007) directly compared the effectiveness
594 of feedback timing on behavior. In this study, a combination of retrospective and concurrent
595 feedback yields greater effect than separate timing strategies, because of the additional
596 informational benefit offered by recurrent feedback on top of the direct intervention in behavior
597 offered by concurrent feedback. Furthermore, Tulusan, Staake, and Fleisch (2012) find that users
598 of their eco-driving support application prefer direct, concurrent feedback over retrospective
599 feedback: the efficacy of the application is significantly predicted by the usage of the direct
600 feedback delivered by the app, but not by retrospective, indirect feedback.

601 **Feedback modality.** Of the papers included in the review, 58 studies offered visual
602 feedback only, one offered auditory feedback only, and 8 studies used tactile feedback only. Five
603 studies directly compared the effectiveness of different feedback modalities, two of which
604 contrasted visual with auditory feedback, one study contrasted auditory with tactile feedback;
605 one study contrasted visual with tactile feedback, and one study compared three feedback modes:
606 visual, auditory and tactile. Studies comparing tactile feedback with other modalities found this
607 modality more effective when aimed at changing motor skills (Maltz & Shinar, 2004; Epstein et
608 al., 2012) and when disruptiveness mattered. Generally, tactile feedback was found to be less
609 disruptive in other tasks compared to auditory feedback, which in turn is less disruptive than
610 visual feedback. A reverse pattern can be observed in the amount of detail that can be

611 communicated through different feedback modalities: visual feedback can be more detailed than
612 auditory, which can offer more detail than tactile feedback (Hoggan & Brewster, 2010). One
613 study (Epstein et al., 2012) reported an effect of feedback modality on the durability of the
614 achieved behavior change: sitting posture was changed beneficially through visual feedback, but
615 only the addition of tactile feedback on optimal posture led to lasting effects.

616 These studies serve as an indication that the optimal selection of feedback modality not
617 only depends on the targeted behavior, but also on the amount of disruption that a given task
618 allows and the necessary detail of the feedback. More evidence to support this assumption is
619 needed.

620 Three papers support the assumption that multimodal feedback is more effective than
621 single-mode feedback (Hoggan & Brewster, 2010; Lieberman & Breazeal, 2007; Quian et al.,
622 2011). In these cases, the increased effect mostly lies in additional strengths of different feedback
623 mode, for example tactile feedback in smartphones being more effective in noisy areas and
624 auditory feedback more effective in silent areas. Maltz and Shinar (2004) tested the concurrent
625 application of visual and auditory feedback in driving behavior and found no beneficial effect of
626 multimodal feedback, leading to the conclusion that auditory feedback is most effective for
627 driving behaviors and other modalities do not add further improvement.

628 ***Feedback frequency and duration.*** The greater part of included studies (67 out of 72)
629 used either continuous or on-demand delivery of feedback, which means almost all studies made
630 use of the possibilities digital technologies offer in delivering the feedback as soon as possible.
631 No studies compared the effect of different delivery frequencies directly. From the current
632 literature, no conclusions can be drawn on the effectiveness of feedback frequency on feedback
633 impact.

634 The duration of the feedback intervention differed from a single trial to one year. Those
635 papers reporting lasting intervention effects had durations of six months (Pellegrini et al., 2012;
636 Schultz et al., 2014), and one year (Ford et al., 2010). However, there is an obvious confound of
637 intervention length with the type of behavior targeted, because not every habitual behavior is
638 equally difficult to change, with periods needed for change ranging from a few weeks to
639 behavioral vigilance without time limit (Lally & Gardner, 2013). Therefore, a single standard of
640 ideal feedback intervention duration and frequency seems conceptually impossible.

641 ***Feedback presentation: Usability and aesthetics.*** Three papers considered the effect of
642 visual design on feedback effectiveness directly. All three found some explorative indication that
643 design and aesthetics matter for feedback acceptance, use of the feedback device and feedback
644 impact. One paper (Consolvo, MacDonald & Landay, 2009) provides a very useful list of
645 directives for the design of feedback presentation. The authors state that feedback should be
646 abstract and reflective, unobtrusive and public, aesthetically pleasing, positive, controllable,
647 trending/historical in comparison, and comprehensive. Two papers (Nakajima & Lehdonvirta,
648 2011); Rodgers & Bartram, 2011) described how heightened abstraction and aesthetic
649 pleasingness seem to come at a cost in terms of usability and comprehension.

650

651 **3.6 Other insights**

652 Close scrutiny of all reviewed studies revealed a couple of noteworthy additional themes
653 that were not detected in the analysis of existing literature that led to the hypotheses posed in this
654 review.

655 One additional theme that emerged is the role of disruption in feedback efficacy.
656 Feedback can play a role in habit change by disrupting the automatic response to a cue.

657 However, this disruption may also cause a task to be abandoned or otherwise disturb task
658 resumption (Bittner & Zondervan, 2015). The amount of disruption therefore needs to be
659 carefully tailored to break the automatic cue-response-chain without abandoning the task
660 altogether. In this analysis, two papers mentioned the role of disruptiveness on feedback effect.
661 As mentioned above in the section on feedback modality, a study of feedback delivered by a
662 mobile game with different feedback modalities (Hoggan, Crossan, Brewster, & Kaaresoja,
663 2009) exhibited an interaction between feedback modality, disruption, and richness of the
664 feedback. Interestingly, one study (Liu & Pfaff, 2014) showed how feedback can also be used to
665 facilitate the resumption of tasks after disruptions.

666 Another important insight is that the amount of integration of feedback in other areas of
667 behavior, such as usage of similar interventions or sharing behavior on online social networks,
668 might be a strong predictor of feedback effect. Wallenborn, Orsini and Vanhaverbeeke (2011)
669 found that when energy monitors are not integrated in pre-existing practices, the information
670 quickly disappears into background noise like with any other new appliance. A study by Jain,
671 Taylor & Pescheira (2012) had a similar finding in a study of the usage of an interface providing
672 feedback on energy consumption. Bentley et al. (2013) found similar patterns in the effect of
673 health mashups. When participants used an app that integrated fitbit activity tracking data with
674 weight, food intake, sleep etcetera, sustained use of the feedback technology increased.

675 This notion of integration is an interesting concept that needs further exploration. Indeed,
676 relevant theories that explain the effectiveness of feedback on behavior change, such as Social
677 Cognitive Theory (e.g. Bandura, 1997) or Control Theory (Kuhl, 1985; Carver & Scheier, 1985),
678 suggest that behavior change is most likely if feedback is not delivered on its own, but embedded
679 in larger interventions with clear target behaviors and action plans. This notion is also backed up

680 by considerable evidence from original research (e.g. Avery et al., 2012; Sniehotta et al, 2006;
681 Godino et al., 2013) and reviews (e.g. Dombrowski et al., 2012; Gardner et al., 2010).

682 Wallenborn, Orsini and Vanhaverbeeke (2011) noted that wasteful behavior in energy use
683 can arise from role perception ("a good parent always gets the laundry clean and therefore
684 washes at 90° C") and different levels of technical insight in families might lead to conflicts
685 about the performance on feedback. This gives insight in how social interactions influence
686 feedback effect. Feedback on performance spurs discussion with family members and others,
687 which may in itself lead to behavior change or even conflicts and role clashes. Similar effects are
688 reported by Kappel and Grechenig (2009) when they mention positive social effects of their
689 device that reports water usage in the shower: "A couple used to argue that one of them always
690 took longer in the shower and (...) used more water. (...) (T)hey learned that the woman used
691 only half as much water, even though she spent more time in the shower. This discovery
692 stimulated the man to further reduce his own water consumption. In another household the child
693 (11 yrs.) triggered discussions about the water consumption, because he used much less water
694 than his parents. This stimulated his mother to begin reducing her own consumption (...)."
695 Nakajima & Lehdonvirta (2013) and Katzeff et al. (2013) found similar results in an intervention
696 aimed at (respectively) children's tooth brushing and energy use in the office.

697 **4. Conclusion**

698 This review shows that in the 72 studies we analyzed, feedback delivered through digital
699 technology is generally effective in disrupting habitual behavior. However, the current literature
700 does not provide enough evidence to support the hypothesis that feedback through digital
701 technology leads to lasting behavior change. Furthermore, little is known about factors that

702 facilitate sustained use of digital technology, intra-personal and inter-personal moderators of
703 feedback efficacy, and the effect of feedback characteristics.

704 This review makes clear that feedback through digital technology has the potential to
705 disrupt undesired habits. Therefore, such feedback can be seen as a potentially reinforcing
706 ingredient for any intervention aimed at habit change. This work offers support for Quantified
707 Self-solutions, which may indeed lead to healthier, more eco-friendly behaviors; it also supports
708 the notion that delivering feedback through digital technology may heighten the chances of
709 conscious scrutiny for a broad range of deeply engrained, undesirable habits. Our analysis shows
710 this finding is consistent across feedback technologies: feedback delivered through a broad range
711 of technological channels appears to succeed in disrupting undesired habits.

712 However, the possibilities of using feedback through digital technology for sustainable
713 habit change have yet to be proven. Particularly, the durability of the feedback effect on habitual
714 behavior is as yet unclear. Those few studies that included longitudinal measurements generally
715 found sustainable effects of feedback on behavior, but the greater part of the studies only
716 measured effects right after the intervention. To prove the hypothesis that feedback through
717 digital technology actually enables users to change their behavior, more evidence on whether the
718 use of the digital technology leads to lasting effects is necessary.

719 To ensure the occurrence of behavior change, intervention designers must make sure their
720 technology is accepted by its users, and used long enough to warrant habit change. Existing
721 literature (e.g. Ledger & McCaffrey, 2014) suggests that technological feedback solutions are
722 often to be discarded after initial use. Unfortunately, methods to maintain engagement with a
723 technology over time remain unclear.

724 The role of moderating traits and demographic factors also remains understudied. Very
725 little is known of the interplay of traits and states on the one hand, and feedback properties such
726 as feedback sign, comparison, and delivery mode on the other. Similarly, the effect of different
727 feedback properties such as timing, modality, frequency and duration, have not yet received the
728 attention needed to draw any conclusions on their impact on feedback effect. This suggests that
729 we cannot yet tell whether changes in behavior can really be attributed to the digital technology
730 and its feedback, or that these are merely functioning as some sort of lens through which only
731 well-motivated and capable individuals manage to focus their behavior-changing endeavors.

732 Although this review provides evidence for the effect of feedback through digital
733 technology on disrupting habitual behavior, this review also demonstrates that research into such
734 effects has only just started. Because of the explorative, descriptive nature of a great part of the
735 included papers, there are limits to the conclusions that can be drawn from this review. The
736 majority of the included quantitative studies, 33 out of 50, did not report any control measures
737 for demand characteristics or other experimental artifacts, e.g. through well-balanced
738 experimental designs. Furthermore, 22 out of 30 quantitative studies with statistical analysis
739 were statistically underpowered, which seriously reduces the validity of any conclusions drawn
740 from those papers. As a consequence, only a part of the 72 original studies in this review (14
741 quantitative studies and 21 qualitative studies) were described in a way that proves enough
742 methodological rigor to act as a source for direct evidence. The literature would benefit greatly
743 from well-performed additional research on the effect of feedback through digital technology on
744 habitual behavior, be it field studies or lab work, with good active controls for experimental
745 artifacts and ample statistical power.

746 Moreover, it remains unknown how many studies did not make the literature because the
747 desired effect could not be shown or no support was found for the original hypothesis. The great
748 majority of studies in this review found a positive effect of feedback on habit disruption, much
749 more so than in similar analyses (e.g. Kluger and Denisi, 1996, who find a 66% success rate).
750 The field (and science in general) would greatly benefit from measures aimed at reducing
751 publication bias, such as pre-registering studies, to provide insight into how many 'failed' studies
752 end up in the proverbial file drawer (Franco, Malhotra, & Simonovits, 2014).

753 The review also shows the merit of combining quantitative research with good qualitative
754 and explorative research. It is paramount that theories of behavior change are supported by well-
755 designed trials, but important insights such as the influence of social interaction on the effects of
756 feedback delivered by digital technology would not easily show up in even the most well-set up
757 quantitative research.

758

759 **4.1 Further research**

760 All of these areas provide ample possibilities for further research. The broad range of
761 dependent variables and feedback technologies limit the validity and generalizability of the
762 findings in this review. However, the results presented here may serve as a basis for further
763 studies and analyses.

764 One such analysis could examine which behaviors are most likely to benefit from
765 feedback delivered through digital technology. Intuitively, the hypothesis that feedback does not
766 affect every habitual behavior equally seems plausible, but evidence is lacking. Similar questions
767 arise when the different technologies are taken into view. Different technologies offer different
768 possibilities for feedback modality and other properties. It seems plausible to assume that these

769 differences influence efficacy, but this does not follow from the results of this review. Particular
770 attention should be paid to the level of disruption of the feedback. Evidence (Bittner &
771 Zondervan, 2015) suggests that feedback may disrupt tasks in such a way that this leads to task
772 abandonment. Some feedback modalities (visual) are clearly more disruptive than others
773 (vibrotactile, auditive). The effects of feedback disruptiveness on sustained performance warrant
774 further scrutiny.

775 Factors moderating the sustained use of technological solutions are another area that
776 deserves our attention. Without use, we cannot expect technology to have any effect on behavior.
777 User experience, usability, and design can be thought of as moderating factors on the effect of
778 feedback, but as yet this hypothesis lacks support. Intuitively, and from what little evidence that
779 exists (e.g. Ludden et al, 2015), one would reason that clunky designs are unlikely to get used,
780 with detrimental consequences. Therefore, we see the lack of focus on usability in this research
781 field as a serious problem. Similar focus is needed on other factors influencing the lasting use of
782 technological feedback solutions. Is a high motivation essential? Do certain personality
783 characteristics facilitate sustained use, and what is the effect of feedback characteristics? All
784 these questions need an answer.

785 Another example of an area of interest that deserves further scrutiny is the effect of
786 personality traits and states such as initial motivation and self-efficacy on feedback impact.
787 Literature suggests that high initial motivation and self-efficacy increase the impact of feedback
788 on habitual behavior. However, results from studies in this paper suggest a ceiling effect. A well-
789 set up experimental design could shed light on the effect of initial motivation and perceived self-
790 efficacy on the effect of feedback on habits.

791 A similar question remains about the effect of feedback sign. In this review, the greater
792 part of the studies provided feedback in such a way that both positive and negative feedback was
793 possible. Unfortunately, this makes it impossible to test an interesting hypothesis, i.e. concerning
794 the interaction between feedback sign and regulatory focus – the tendency to approach positive
795 impulses and avoid negative ones. Van Dijk and Kluger (1994, 2011) suggest that in a
796 prevention focus (avoiding negative consequences), negative feedback should have more effect,
797 whilst in a promotion focus (approaching positive consequences), positive feedback should have
798 more effect. Hattie and Timperley (2007) however, find in a meta-analysis that positive feedback
799 should always lead to more effect than negative feedback. This issue is particularly relevant to
800 feedback delivered through digital technology, which by nature is capable of delivering both
801 signs, depending on individual performance. Is feedback more effective in a prevention focus as
802 long as goals are being reached, and does it lose its effect when goals are too hard - and
803 similarly, is feedback more effective in a prevention focus as long as goals are not reached yet?
804 Further research could give valuable insights in when feedback through digital technology has
805 the most effect.

806 In a similar vein, the optimal choice of feedback properties in such a way that feedback is
807 delivered concurrently with behavior in a continuous or on-demand manner, and data gathering
808 for the feedback takes place automatically without the need for self report measures, should
809 intuitively lead to an enhanced feedback efficacy. This hypothesis, however, remains
810 unsubstantiated. Subjects of similar interest that have not been researched in a controlled manner
811 at all are the active integration of feedback through digital technology within more complex
812 interventions, and the social effects of digital technology. In real-life situations, feedback is not
813 delivered in a vacuum, but plays a role in a social practice. Users will interact with friends,

814 family and others about the received feedback, the attainability of goals, and the use of the
815 artifact that delivers the feedback. The effects of feedback integration and social practices on
816 feedback efficacy are in urgent need of research.

817 Further research into the effectiveness of feedback interventions to disrupt habits,
818 personal differences in feedback efficacy, and the effect of applying different feedback
819 characteristics, might not only enhance our knowledge on how habits might be changed. Such
820 research would also serve as a basis for intervention developers and designers to inform the
821 design of more effective behavior change products. The ubiquity of Quantified Self-solutions
822 and health-related apps on smartphones show a great level of acceptance of this kind of
823 intervention. The public is generally ready and willing to embrace such interventions. Badly set-
824 up products without a base in scientific evidence might do lasting damage to the benevolent
825 reception feedback interventions currently receive. But well-designed, evidence-based solutions
826 can be expected to have a great impact on our well-being and on the proliferation of sustainable
827 behavior. Feedback through digital technology as an intervention strategy to change undesirable
828 habitual behavior offers great chances for healthier and more sustainable living that should not
829 be wasted.

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