

1 **Understanding and Promoting Effective Engagement with Digital Behavior Change**
2 **Interventions**

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27 **Abstract**

28 This paper is one in a series developed through a process of expert consensus to provide an
29 overview of questions of current importance in research into engagement with digital
30 behavior change interventions, identifying guidance based on research to date and priority
31 topics for future research. The first part of this paper critically reflects on current approaches
32 to conceptualizing and measuring engagement. Next, issues relevant to promoting effective
33 engagement are discussed, including how best to tailor to individual needs and combine
34 digital and human support. A key conclusion with regard to conceptualizing engagement is
35 that it is important to understand the relationship between engagement with the digital
36 intervention and the desired behavior change. This paper argues that it may be more valuable
37 to establish and promote ‘effective engagement’, rather than simply more engagement, with
38 ‘effective engagement’ defined empirically as sufficient engagement with the intervention to
39 achieve intended outcomes. Appraisal of the value and limitations of methods of assessing
40 different aspects of engagement highlights the need to identify valid and efficient
41 combinations of measures to develop and test multidimensional models of engagement. The
42 final section of the paper reflects on how interventions can be designed to fit the user and
43 their specific needs and context. Despite many unresolved questions posed by novel and
44 rapidly changing technologies, there is widespread consensus that successful intervention
45 design demands a user-centered and iterative approach to development, using mixed methods
46 and in-depth qualitative research to progressively refine the intervention to meet user
47 requirements.

48

49 **Introduction**

50

51 Engagement with health interventions is a precondition for effectiveness; this is a particular
52 concern for digital behavior change interventions (DBCIs), i.e., interventions that employ
53 digital technologies such as the internet, telephones and mobile and environmental sensors.¹
54 Maintaining engagement can be especially difficult when DBCIs are used without human
55 support, typically leading to high levels of dropout and ‘non-usage attrition’,^{2,3} whereby
56 participants do not sustain engagement with the intervention technologies. This paper
57 discusses current approaches to conceptualizing and measuring engagement, and considers
58 key issues relevant to promoting effective engagement.

59

60 This paper is one in a series developed through a process of expert consensus to provide an
61 overview of questions of current importance in research into engagement with DBCIs, and to
62 identify outstanding conceptual and methodological issues.¹ An international steering
63 committee invited established and emerging experts to form a writing group to contribute to
64 this process. The scope, focus and conclusions were formulated initially by the committee and
65 writing group, and then further discussed and modified with input from 42 experts
66 contributing to a multidisciplinary international workshop. As such, the paper is necessarily
67 selective and does not exhaustively review the relevant literature or propose particular models
68 or solutions, but provides a critical reflection on the state-of-the-art. The insights gained from
69 this process are summarized in the concluding table as guidance based on research to date and
70 priority topics for future research.

71

72 Some of the insights into engagement that emerged are specific to DBCIs, which have

73 features that are not shared with other forms of intervention delivery – in particular, the
74 potential to automatically record and respond to how the user is engaging with the
75 intervention. However, many of the challenges confronting DBCI use are shared with other
76 types of intervention -- for example, the need for users to engage with the behavior change.
77 Consequently, the unique potential of DBCIs to record engagement and behavior in detail
78 over time is likely to generate important new insights that have relevance to engagement with
79 other behavior change interventions.

80 **Understanding Engagement**

81

82 *Conceptualizing Engagement*

83 The term ‘engagement’ has been used in different ways in engagement research, making it
84 challenging to synthesize the models and measures that have been proposed. Some
85 researchers focus principally on engagement with digital technology, drawing on disciplines
86 such as Human-Computer Interaction, psychology, communication, marketing, and game-
87 based learning.⁴ In this approach, engagement is typically studied in terms of intervention
88 usability and usage, and factors that influence these. For example, O’Brien & Toms define
89 engagement as a quality of users’ experiences with technology; they identify dimensions of
90 challenge, aesthetic and sensory appeal, feedback, novelty, interactivity, perceived control and
91 time, awareness, motivation, interest, and affect.⁵ Other researchers approach DBCIs as a
92 specific method of delivering health interventions, viewing engagement with DBCIs as
93 similar to engagement with face to face interventions. This approach focuses on users’
94 engagement with the process of achieving positive cognitive, emotional, behavioral and
95 physiological change. It draws on evidence-based therapeutic principles (such as cognitive-
96 behavioral therapy), existing behavioral theories (such as social cognitive models) and
97 research on broader engagement processes (such as the therapeutic alliance and social

98 support). For example, key design features of DBCIs identified by Morrison et al. include
99 social context and support, contacts with the intervention, tailoring, and self-management.⁶

100

101 To understand and analyze the relationship between engagement with technology and
102 behavior change it may be helpful to distinguish between the ‘micro’ level of moment-to-
103 moment engagement with the intervention and the ‘macro’ level of engagement and
104 identification with the wider intervention goals, while appreciating that these are intimately
105 linked. Figure 1 illustrates how engagement with the DBCI and the behavioral goals of the
106 intervention may vary over time. Engagement is a dynamic process that typically starts with a
107 trigger (e.g. recommendation by health professional or peers), followed by initial use, which
108 may be followed by sustained engagement, disengagement or shifting to a different
109 intervention. The timing of and relationship between the different forms of engagement will
110 vary depending on the intervention, the user and their context.

111

112 Some engagement models attempt to encompass the full range of factors that may influence
113 engagement with both the digital technology and the health-related behavior change. For
114 example, the Behavioral Intervention Technology model⁷ builds on and integrates several
115 other relevant models,⁸⁻¹¹ providing a framework for articulating the relationship between the
116 behavioral intervention aims, elements, characteristics, and workflow and the technological
117 methods of implementing the intervention. New interdisciplinary models of engagement are
118 emerging but are largely untested; consequently, their validity is not yet established. Some
119 authors have used literature review to identify retrospectively which factors are associated
120 with success of DBCIs,^{6,12-14} but the strength of the conclusions that can be drawn is limited
121 by the correlational nature of the evidence and incomplete descriptions of the interventions.
122 Establishing which elements of these models are most influential on engagement is therefore

123 a key research priority, and new theoretical frameworks and models may need to be
124 developed (as discussed elsewhere in this issue).¹⁵ Taxonomies of features specific to DBCIs
125 (such as digital delivery methods¹⁰) may prove useful for this purpose; for example,
126 taxonomies have helped to clarify what types of supplementary support are associated with
127 positive DBCI outcomes,¹⁶ what features of computerized clinical decision support systems
128 are effective,¹⁷ and the importance of feedback in weight management DBCIs.¹⁸

129

130 User engagement is also supported, undermined or shaped by socio-contextual influences,
131 such as the role played by family members and the broader cultural setting. Comprehensive
132 models of engagement need to encompass not only individual-level user dimensions but also
133 the effects – positive and negative – of social dimensions. For example, technologies can
134 harness social support by sharing behavioral tracking and/or promoting encouragement from
135 peers,¹⁹ but some users may be less likely to commit to behavioral goals if they will be
136 publicly shared.²⁰

137

138 A crucial implication of explicitly recognizing the distinction between engagement with the
139 technological and the behavioral aspects of the intervention is that intervention usage alone
140 cannot be taken as a valid indicator of engagement. In the absence of agreed definitions and
141 well-validated theoretical models of engagement, much previous research has operationalized
142 engagement as the extent to which people use the digital intervention as intended,¹³ on the
143 assumption that usage is closely related to outcome. There are several problems with this
144 assumption. Firstly, the evidence that usage is associated with intended outcomes is mixed,
145 and largely correlational.²¹⁻²³ It is difficult to determine to what extent usage mediates
146 behavioral and health-related outcomes, as this may be confounded by common factors such
147 as higher motivation and self-regulation skills. Usage metrics also reveal little about offline

148 engagement with intervention content, which is important in interventions that require
149 homework outside the context of the digital intervention. A further complication is that
150 cessation of usage could indicate disengagement from an intervention, or could signal
151 sufficient mastery that continued access to the digital technology is no longer needed (see
152 Figure 1). Continued engagement might indicate positive, healthy engagement with the
153 intervention content or, conversely, dependence on the guidance or feedback, and thus a lack
154 of successful self-regulation. Rather than focus on ‘engagement’, it would be beneficial to
155 focus on ‘effective’ engagement that mediates positive outcomes; this may or may not require
156 sustained engagement. Effective engagement is thus defined in relation to the purpose of a
157 particular intervention, and can only be established empirically, in the context of that
158 intervention. A further consideration is that users may value different outcomes from those
159 intended by designers;²⁴ for example, a DBCI may not achieve behavior change but may
160 provide valued information, reassurance or opportunities for interaction.

161
162 In summary, a key research challenge is to conceptualize engagement more consistently,
163 comprehensively and dynamically, taking into account user experiences of the technology and
164 the social and therapeutic context. The next step is not simply to propose but to test and
165 validate models of effective engagement by demonstrating which elements of these models
166 positively influence different aspects of engagement and mediate outcomes. The following
167 section explains how the multidimensional nature of effective engagement can be captured by
168 using complementary methods of assessment.

169

170 *Evaluating Engagement*

171

172 A range of methods is available to measure effective engagement (see Table 1) that offer

173 complementary insights into different dimensions of engagement, and can be used at different
174 stages of intervention development, evaluation, and implementation. These include reports of
175 the subjective user experience, elicited by qualitative methods or questionnaires, and
176 objective measures of technology usage, user behavior, and users' reactions to the
177 intervention.

178

179 In-depth qualitative analyses of user experiences can capture critical information about how a
180 user reacts to the content and design of DBCIs and offer explanations for why the user
181 interacts with a DBCI in particular ways. These data enable researchers to explain objective
182 usage patterns more reliably and generate hypotheses about the factors influencing effective
183 engagement that can be tested using other methods. Qualitative analyses can capture critical
184 information about offline behavior (particularly engagement with the behavioral target of the
185 intervention) and the wider social and contextual influences on engagement.²⁵ Qualitative
186 methods can also reveal aspects of engagement with the technology that may not be captured
187 by quantitative usage data – such as “lurking,” a common phenomenon whereby users read
188 and may benefit from the content in online social communities but do not actively interact
189 with the digital intervention.^{26,27} Typical qualitative methods include focus groups,
190 interviews, observation of user interaction with the intervention (which might include users
191 ‘thinking aloud’ while using the intervention), diary studies and retrospective interviews.²⁸
192 Given the increasing reliance on participant involvement in DBCI design, it is vital that
193 research clarifies what users are able to report accurately. For example, users can usually
194 identify aspects of a DBCI that they dislike or describe their views and behavior, but few
195 users can prospectively anticipate factors that will encourage effective engagement with
196 DBCI content or retrospectively recall their reasons for engagement or disengagement.

197

198 Self-report questionnaires can also measure dimensions of engagement (including off-line
199 engagement) that cannot be assessed objectively. Questionnaires to retrospectively assess
200 engagement with DBCIs at selected time points are available.²⁹ Alternatively, ecological
201 momentary assessment (EMA) enables immediate, repeated measurement of users'
202 experiences with interventions in-the-moment.³⁰ A dilemma for self-reporting is to balance
203 the need to measure all relevant dimensions of engagement with the response burden for
204 users, which may also lead to measurement effects such as response shift and be an
205 intervention in itself. While a solution may be to develop validated instruments to measure
206 engagement within a specific setting, the use of different questionnaires for each study would
207 limit cross-study comparisons. Further research is also required to establish the validity of
208 questionnaires assessing engagement in terms of predicting outcomes.

209
210 Qualitative insights and questionnaire data can be complemented by proxy measures of
211 engagement based on usage.³¹ These can include the number of visits/uses, modules or
212 features used, time spent on the intervention, number and type of pages visited, or response to
213 alerts or reminders.³² Usage metrics can provide valuable insights, but are typically large,
214 complex datasets that are challenging to interpret. For example, additional qualitative data can
215 be needed to provide explanations for observed differences in usage metrics between
216 participants or intervention groups.³³ Recent advances in sequence analysis, data mining, and
217 novel visualization tools are facilitating analyses of usage patterns and there is scope for
218 substantial progress in this field.²³ DBCIs have the potential to generate datasets sufficiently
219 large to be able to reliably model and experimentally test³⁴ mediation of outcomes by
220 engagement with particular intervention components and to statistically control for
221 confounding moderator effects such as baseline motivation levels.^{22,26,35,36} Importantly, usage
222 metrics can be collated with data on users' behavior collected by Smartphone sensors, such as

223 movement or location.³⁷ However, more studies are needed to establish what features or
224 correlates of engagement sensor data can capture reliably and new statistical approaches will
225 be required to analyze these large and complex datasets. The novel research designs that can
226 support these analyses are discussed in companion papers in this issue.^{15,34,38}

227

228 Psychophysiological measurements, ranging from skin conductance and heart rate to facial
229 expression or fMRI, have been used to measure users' task-engagement.³⁹ Such measures can
230 help identify aspects of the intervention that attract attention or evoke emotional arousal,
231 suggesting mechanisms through which DBCI content or design impact short term
232 engagement. These surrogate measures of engagement can be difficult to interpret and
233 differences in attention may not always translate into differences in intervention use (or other
234 measures of engagement)⁴⁰. That said, they do complement subjective measures by providing
235 an objective measure of user reactions.

236

237 To summarize, effective engagement can only be understood through valid, reliable and
238 comprehensive means of assessment. Adopting a mixed method multidimensional approach
239 will provide a more comprehensive picture of how (well) users are engaging with DBCIs⁴¹,
240 but can pose problems of resource constraints and user burden, particularly when
241 interventions are implemented 'in the wild'. The complementary value of different
242 approaches for understanding effective engagement remains to be clarified; further work is
243 needed to determine the most accurate and efficient combinations of assessments, and to
244 understand better how to compare and integrate the data, inferences, and outcome
245 relationships derived from complementary measures that tap into different aspects of
246 engagement.

247 **Promoting Effective Engagement**

248

249 This section first introduces techniques for promoting effective engagement, identifying
250 substantive gaps in knowledge and directions for future investigation, and then considers two
251 key topics in engagement research: tailoring to individual needs (including the needs of those
252 with lower levels of literacy and computer literacy); and combining DBCIs with human
253 support.

254

255 *Promoting Effective Engagement*

256 Promoting effective engagement requires interventions to be perceived as having benefits that
257 outweigh their costs – including the ‘opportunity costs’ of engaging in other valued activities.
258 The benefits can be affective or functional, meaning that DBCIs may be valued because they
259 create an intrinsically enjoyable user experience (such as health-promoting games) or because
260 they are seen as meeting evidence based therapeutic principles and users’ needs (such as
261 online cognitive-behavioral therapy). In the latter case, users may engage even if they are not
262 enjoyable. To fully appreciate users’ needs and perspectives it is essential to involve the target
263 population in intervention development.

264

265 Structured methods to guide intervention development which emphasize the importance of
266 engaging end users have been developed. The aim of user-centered design is to ground the
267 development of all digital products in an understanding of the user’s knowledge, skills,
268 behavior, motivations, culture and context.⁴² The ‘person-based approach’ to digital health
269 intervention development⁴³ provides a complementary health-related behavioral science
270 focus, emphasizing user views of the behavior change techniques the intervention is intended
271 to support, both online and offline. There is considerable convergence in views of the process
272 needed to achieve high quality DBCIs. An iterative development and evaluation process, with

273 repeated use of applied methods to engage stakeholders, is needed to progressively refine the
274 intervention to meet user requirements; hence, qualitative methods are central to
275 understanding how to improve user engagement with the technology and the behavior change.

276

277 To date, engagement research has tended to be pragmatic, focusing on addressing the specific
278 engagement-related issues arising in the context of a particular intervention. The field could
279 benefit from more systematic attention to methodological issues; for example, the preceding
280 discussion suggests it may be more fruitful to focus on promoting effective rather than
281 sustained engagement. An additional challenge is that different forms of technology are
282 engaged with in different ways. For example, the portability of smartphones and wearables
283 offers exciting opportunities for ‘just-in-time’ intervention, but those interventions are likely
284 to be used in distracting environments, for brief periods, using small screens and keyboards.
285 Methods of achieving effective engagement need to be developed to accommodate the various
286 technologies used and where and when they are used. Consideration also needs to be given to
287 how best to combine the iterative qualitative process of refining engagement with new,
288 quantitative methods of evaluating the effectiveness of DBCI ingredients.^{35,39}

289

290 *Tailoring and Fit*

291 Engagement with DBCIs has typically been greater among those with higher levels of
292 education and income.³ However, recent improvements in digital access in lower income
293 countries and to all sociodemographic groups mean that it is timely and important to consider
294 the extent to which it may be necessary to tailor DBCIs to ensure they are accessible and
295 engaging for people with lower levels of education, literacy or computer literacy.⁴⁴
296 Interventions to improve health literacy have included using simple language, presenting
297 information in audio-visual formats, tailoring content to individual needs, and other forms of

298 interactivity.⁴⁵⁻⁴⁷ These approaches have shown promise for improving knowledge and self-
299 management, but the evidence is inconclusive, few studies have been theory-based, and it
300 remains unclear whether different intervention elements engage and optimize outcomes for
301 people at varying levels of health literacy.⁴⁸ There is some evidence that intervention design
302 formats that are accessible and engaging for people with lower levels of health literacy may
303 also be acceptable and usable by people with higher levels.⁴⁹ If confirmed, those findings
304 suggest that DBCIs for all can be designed to be accessible and engaging for those with low
305 health literacy. Involving people from lower income backgrounds in research poses
306 challenges that need to be overcome in order to better understand their needs and barriers.
307

308 Further research is also needed to understand how to design interventions to support people
309 with particular attributes. Market segmentation informs most product design, but the ‘market’
310 for DBCIs is relatively immature, and understanding of the factors that influence engagement
311 with DBCIs is correspondingly immature. Factors likely to shape people’s engagement with
312 DBCIs include their lifestyles and what interests and motivates them. For example, an
313 intervention to help an individual with mobility difficulties who is frightened of causing
314 injury and pain will look and feel different from one designed for an injured athlete wanting
315 to get back to full fitness. Within any market segment, there is then scope for allowing users
316 to tailor the intervention to their particular situation and requirements. Moreover, adaptive
317 interventions should permit tailoring for individual differences to be supplemented by
318 ‘within-person’ tailoring as the individual’s needs and status change.¹⁵ Context sensing (using
319 mobile or environmental sensors to detect features of the person’s current behavior and
320 circumstances) should enable timely delivery of content and notifications tailored to the
321 individual’s immediate situation⁵⁰; for example, activity sensors have been used successfully
322 to detect sedentary behavior and prompt physical activity breaks. While context-sensing

323 should increase engagement by enhancing the perceived attunement of the intervention,
324 limited research has yet examined this assumption due to the novelty of this technology.⁵¹

325
326 Tailoring digital intervention delivery and content to users' needs, motivations and personal
327 characteristics enables users to receive guidance that is appropriate, relevant and safe for
328 them. Tailoring can have a positive impact on intervention outcomes and engagement, but this
329 varies between studies and contexts.^{31,52} Self-determination theory,⁵³ a prominent theory of
330 motivation, argues that autonomy is a fundamental human need that facilitates learning.
331 Hence fostering autonomy by giving users personal choices throughout an intervention should
332 be motivating.⁵⁴ A major benefit of digitally delivered interventions is the possibility of
333 offering recipients a choice of formats and tools, allowing users to 'self-tailor', selecting what
334 they find most accessible, attractive and useful. Nevertheless, conventional tailoring of
335 content to match an individual's demographic characteristics^{55,56} may still be required to
336 ensure that users are not presented with material they find so alienating or demotivating that
337 they abruptly cease using the intervention. In summary, tailoring can be valuable, but the
338 optimal balance between tailoring and self-tailoring in different contexts requires further
339 investigation.

340

341 ***Combining Digital and Human Support***

342 Adding human facilitation can improve effective engagement with DBCIs, but there is
343 considerable heterogeneity in findings; few studies directly contrast different levels of support
344 and comparing across studies is problematic.⁵⁷⁻⁶¹ Moreover, unguided interventions can also
345 be effective, although effect sizes are usually smaller. It is important to establish when human
346 support adds value, since unguided interventions can be disseminated more easily at lower
347 cost and could therefore have huge impact at a population health level.

348
349 Variations in findings regarding benefits of human facilitation may reflect different health
350 needs and preferences of users which, in turn, may vary depending on the types of
351 intervention and facilitation offered.⁶² Simple interventions that users are confident to
352 implement without support may not benefit from additional facilitation.⁶³ Human facilitation
353 may be more important when users feel the need for an expert to reassure, guide or
354 emotionally support them, or hold them accountable. The need for human facilitation may
355 diminish for certain conditions as interventions incorporate elements that make them
356 increasingly user friendly, adaptive, persuasive, even enjoyable, or able to reproduce the
357 required elements of a therapeutic relationship. Further research is needed to identify what
358 features diminish the need for human involvement in delivering DBCIs.

359
360 The ‘supportive accountability’ conveyed by having a benevolent but expert human coach
361 maintain surveillance of the participant’s interactions, is usually valuable to maintain
362 motivation and adherence to intervention requirements.⁶⁴ Human facilitation by peer
363 counselors may help as well, creating a supportive community and affirming that the
364 intervention has been found relevant and feasible by others facing similar health problems.
365 However, integrating DBCIs with healthcare delivered in person can be challenging. Too
366 often the development of DBCIs has been carried out without the involvement of clinicians or
367 attention to how the digital intervention may impact the health professional’s activities, roles
368 and interactions with patients. To maximize clinician engagement, clinicians should be
369 confident that the intervention extends and complements their ability to provide efficient and
370 effective care.⁶⁵ Few studies have taken a holistic approach towards designing for service
371 delivery, in addition to designing for the individual recipient of the intervention. There is an
372 urgent need for techniques to co-design DBCIs so that they re-engineer clinician–patient–

373 family interactions to improve engagement.

374

375 A final topic requiring more investigation concerns the optimal format to integrate human
376 facilitation with digital interventions. Clinician referral to a DBCI enhances engagement,
377 compared to interventions being simply made freely available over the internet or as apps;⁶⁶
378 this suggests that positive endorsement and follow-up by a familiar health professional
379 promotes trust in the intervention. However, remote (telephone, e-mail, or text) coaching to
380 help the user implement the intervention can also be effective,⁶⁷ even without the referral or
381 endorsement of a clinician. This model of provision makes it feasible and cost-effective to
382 offer skilled support by facilitators who have experience of working with the digital
383 intervention. In summary, further research is needed to understand better the nature, timing
384 and extent of support required in different intervention contexts.

385

386 **Concluding Comments**

387

388 Significant progress has been made in recent years in understanding the nature of and
389 requirements for engagement, and particularly in recognizing the importance of carrying out
390 in-depth mixed methods research into how people engage with DBCIs. Table 2 summarizes
391 key guidance points emerging from research to date and highlights areas for further work.
392 Future research would benefit from defining engagement more consistently and appropriately,
393 appreciating that more engagement does not necessarily equate to more effective engagement.
394 Research priorities include empirically testing models of how technological and behavioral
395 elements combine to influence effective engagement, using engagement-related taxonomies to
396 accumulate knowledge and identify mechanisms of action. Comprehensive model testing will
397 require developing and validating complementary objective and subjective measures of

398 engagement, including non-intrusive methods that can be easily implemented without creating
399 user burden or reactivity. Using these models and measures, researchers will then be able to
400 tackle important questions relating to the implementation of DBCIs, such as: how best to
401 involve users, developers, health care professionals, and family in co-design; how to utilize
402 new forms of delivery; how to design interventions that are accessible to those with lower
403 levels of education or income; and when and how interventions need to be adapted for the
404 individual or supplemented by human support.

405

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412

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625 **Figure 1.** Illustration of the ‘micro’ and ‘macro’ levels of intervention engagement.

626 *Note:* This hypothetical example illustrates one way in which engagement with the
627 technology and the behavior change could vary over time; patterns of engagement will
628 vary widely with different interventions and individuals.