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 model[7] 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 methods[10]) 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 test[34] 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 DBCIs[41],

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 development[43] 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 situation[50]; 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

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.