May - August 2020

Rapid Review examining Engagement within Self-Guided Digital Behaviour Change Interventions

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Table of Contents

Introduction

The availability of Digital Behaviour Change Interventions (DBCIs) has increased significantly over the years (Perski, Blandford, West & Michie, 2017). The growth of DBCIs is being fueled by the promise and potential that these interventions show, with research demonstrating the positive impact DBCIs can have. Amongst individuals, DBCI's have shown to improve the health and well-being of the user, successfully targeting a wide array of behaviours, including addiction (Rooke, Thorsteinsson, Karpin, Copeland & Allsop, 2010), diet, exercise (Roberts, Fisher, Smith, Heinrich & Potts, 2017) and mental health (Alqahtani, Al Khalifah, Oyebode & Orji, 2019). On a societal level, the use of DBCI's could lead to significant public health improvements, decreasing the financial and labour force burden on health care systems (Anderson, Burford & Emmerton, 2016; Holdener, Gut & Angerer, 2020).

However, the impact of DBCI's does not momentarily mirror their potential, as the promise and effectiveness of DBCI's are largely dependent on individuals using and engaging with the intervention (Perski, Blandford, West & Michie, 2017). Research studies investigating engagement rates have shown that as little as 10% to 24% of recruited participants were engaged with the intervention at the end of data collection (Druce, Dixon, & McBeth, 2019). These engagement rates are based on research studies where engagement is higher, due to incentives that come with participating in a research study. It has been predicted that the real-life use of DBCI's is significantly lower. Therefore, a key challenge for DBCIs is increasing user engagement (Becker, Miron-Shatz, Schumacher, Krocza, Diamantidus & Albrecht, 2014).

Digital Behaviour Change Interventions

DBCI's "employ digital technologies to encourage and support behaviour change that promotes and maintains health through primary or secondary prevention and management of health problems" (Yardley, Choudhury, Patrick & Michie, 2016). These interventions are complex and commonly employ an array of interacting components and techniques (Asbjørnsen, Smedsrød, Nes, Wentzel, Varsi, Hjelmesæth & van Gemert-Pijnen, 2019), with evidence and theory-based DBCIs commonly implementing Behaviour Change Techniques (BCTs) and Persuasive System Design (PSD) principles.

BCTs are the intervention's 'active ingredients', which evoke behaviour change within individuals (Michie & Johnston, 2012). The use of BCTs within interventions marks a significant development within the field (Atkins et al., 2017). Previously, researchers adopted a single theoretical approach (i.e. health belief model, social cognitive model, the theory of planned behaviour) to guide their interventions (Atkins et al., 2017). With the introduction of BCTs, which stem from behavioural theories and models, an integrative approach to behaviour change is being gradually adopted, which has been found to be more successful (Atkins et al., 2017; Davis, Campbell, Hildon, Hobbs & Michie, 2015). Michie et al., (2011) identified 43 BCTs that were classified into four functions: 1) directly addressing motivation, 2) maximising self-regulatory capacity or skills, 3) promoting adjuvant activities, 4) supporting other BCTs.

Central to digital interventions is the use of technology as the platform for their intervention. However, technology can be utilised further and can be designed with the purpose to bring about behaviour and attitude change, and this is referred to as Persuasive Technology (Orji & Moffatt, 2018). Lehto & Oinas-Kukkonen (2012) introduced a framework to classify the technology in it's persuasive functions.

The PSD model classified features of technology into four different groups: 1) primary task support, 2) dialogue support, 3) social support, 4) credibility support.

Although BCT and PSD principles are different, with BCTs emerging from the field of behavioural psychology and PSD from technological research, the techniques share significant overlap and they are often implemented together (Kelders, Kok, Ossebaard & Van Gemert-Pijnen, 2012). Existing reviews have concluded that the most successful digital intervention uses a combination of BCTs and PSD principles to achieve the most successful behaviour change (Asbjørnsen et al., 2019). By applying Michie's BCTs Taxonomy (Michie et al., 2011) and Oinas-Kukkonen PSD model (2012), the features which are most frequently implemented within DBCI's can be identified and utilised to examine their possible influence on user engagement (Kelders et al., 2012).

DBCIs can differ depending on the level of professional guidance made available to the user. Guided interventions are supported by professionals (therapists, clinicians, coaches) through digital channels embedded within the intervention, such as messaging and video conferencing. Self-guided digital health interventions are independent, running without the guidance and/or support of a professional (Bishop, 2018). Variations in guidance present within interventions reflect the different health and personal needs of users (Karekla et al., 2019). Self-guided platforms tend to be more preventative in nature, targeting behaviour that does not require the help of a clinician (Mehrotra, Kumar, Sudhir, Rao, Thirthalli & Gandotra, 2017). Self-guided interventions have numerous benefits when compared to guided interventions. They are widely accessible, cost-effective, provide treatment access without waiting, and overcome stigma-induced barriers by providing anonymity (Karekla et al., 2019). Despite these benefits, user engagement is significantly lower within self-guided interventions (Kohl, Crutzen & de Vries, 2013).

Although numerous factors contribute to the differences in user engagement, for instance personal agency (Yeager & Benight, 2018) and having more significant baseline symptoms (O'Connor, Hanlon, O'Donnell, Garcia, Glanville & Mair, 2016), Baumeister, Reichler, Munzinger & Lin's (2014) systematic review found that digital interventions with therapeutic guidance have significantly lower drop-out rates in comparison to self-guided interventions. Researchers have proposed that the therapeutic alliance and social support that a therapist provides fosters engagement (Yardley et al., 2016). Additionally, the presence of a therapist influences the effectiveness of several BCT's, most notably the feedback and monitoring of behaviour. When a professional is involved, users feel more accountable to adhere to the intervention (Karekla et al., 2019).

The presence of guidance significantly influences user engagement, distinguishing between self-guided and guided apps in research investigating engagement is largely absent. This lack of differentiation is an evident short-coming present within existing reviews (Kelders et al., 2012). It is crucial to distinguish between self-guided and guided interventions to better understand the relationship between self-guided DBCI's and user engagement. This will allow researchers and practitioners to be informed regarding what interventions elements they should implement to build user engagement in self-guided interventions.

DBCI User Engagement

The definition and conceptualization of DBCI engagement varies depending on the discipline and researcher that studies it. This was illustrated by Doherty & Doherty's (2018) systematic review results where they encountered 102 different definitions and 372 theoretical underpinnings of engagement across 351 papers. DBCI engagement is primarily studied by two disciplines, the behavioural and computer sciences. The behavioural sciences conceptualize engagement primarily in behavioural terms, defining user engagement as the usage of the platform that the intervention is on (Perski et al., 2017). The focus is on the temporal patterns (frequency, duration) and depth (use of specific intervention content) of usage (Perski et al., 2017). There are limitations with this conceptualization, as the focus on the behavioural aspect of engagement is argued to be reductionist, oversimplifying the concept of engagement (Weston & Astley, 2019). Although operationalizing engagement from this perspective is efficient, as digital platforms can record the user's activity, it does not record the depth and focus of their engagement and reveals little on the user's offline engagement (Yardley et al., 2016).

Within the field of Computer Science and Human-Computer Interaction (HCI) engagement is conceptualized as a subjective experience (Perski et al., 2017). Their definition of engagement stems from flow theory (Csikszentmihalyi & Csikszentmihalyi, 1990). Flow refers to "the state in which people are so involved in an activity that nothing else seems to matter; the experience itself is so enjoyable that people will do it even at great cost, for the sheer sake of doing it" (Csikszentmihalyi & Csikszentmihalyi, 1990). Engagement is viewed as "a subset of flow" (Webster & Ahuja, 2004), as these concepts share common attributes, such as focused attention, feedback, control, activity orientation and intrinsic motivation (O'Brien & Toms, 2008).

HCI literature also draws upon an individual's cognition and emotion whilst engaging with the app. Individuals that are engaged are characterized by cognitive absorption, and direct emotions towards the interventions (Perski et al., 2017). Within this field, engagement data is primarily collected through self-reporting, observations, interviews and occasionally physiological data (Doherty & Doherty, 2018). This abstract approach poses a challenge to measuring engagement. How does one identify when an individual is cognitively and emotionally engaged with an intervention?

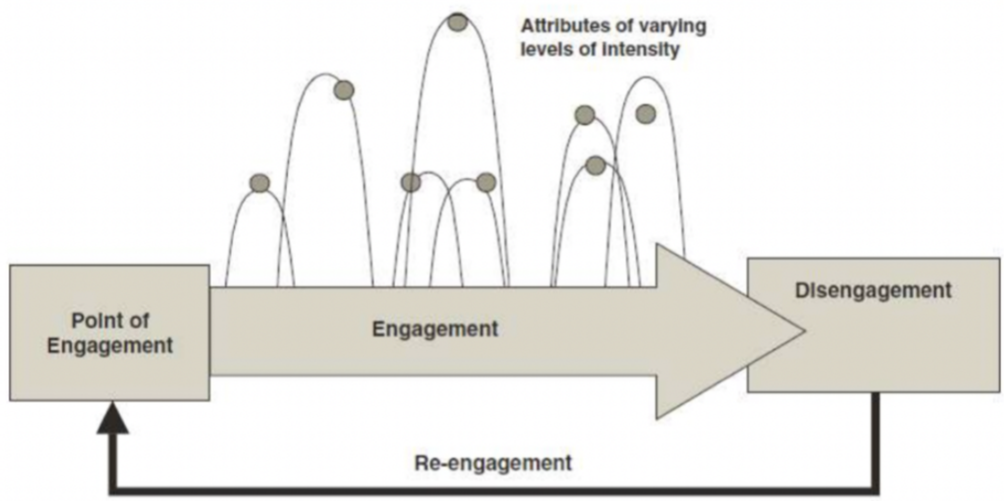
The lack of a universal definition creates challenges for researchers as measuring and operationalizing engagement may differ between studies, impacting the validity and reliability of the research. Significant steps towards a universal definition were made by Perski et al. (2017) following a systematic review of engagement literature from both disciplines. They defined engagement with DBCI's as "the extent (e.g. amount, frequency, duration, depth) of usage" and as "a subjective experience characterised by attention, interest and affect". Whether this definition will be largely adopted by researchers is to be determined, yet it holds various strengths. The definition draws upon the emotional, cognitive and behavioural aspects of engagement (Lalmas, O'Brien & Yom-Tov, 2014), which were defined by Kelders & Kips (2019) as the building blocks of engagement. Additionally, Karekla et al., (2019) highlighted that it captures both the direct (content), and indirect (beliefs about the intervention) influences on engagement. This aligns with Yardley et al., (2016) who postulated that engagement occurs at both a micro (moment-to-moment engagement with the intervention) and macro (identification with the wider intervention goals) level within an individual.

Although Perski et al's., (2017) definition has multiple strengths, it does not acknowledge the full complexity surrounding engagement, such as the different dimensions and the societal influences on engagement.

Engagement lies on a continuum, occurring at different stages as depicted in Figure 1. The level and intensity of engagement within each stage also vary (O'Briens & Tom, 2008). Different factors can influence engagement at every stage. For example, the factors that influence the adoption and adherence to DBCI's vary. The timeline of these different forms of engagement will change depending on the intervention, specifically the content of the intervention, and the user (Yardley et al., 2016). Societal and cultural factors also influence engagement, especially when initiating the use of the app. If the use of technology or self-help tools is not accepted at a societal level, engagement at an individual level is impacted (Sharpe, Karasouli & Meyer, 2017).

In sum, engagement is a complex, multi-faceted, multi-disciplinary, multi-level and multi-temporal phenomenon. These complexities should be considered when reviewing engagement literature as it may impact the findings and generalisability of the research.

Figure 1. The Stages of Engagement



Aim of the Rapid Review

The main goal of the rapid review was to summarise past work conducted on DBCI engagement to address the following two research questions:

1. What factors facilitate engagement within self-guided DBCIs?
2. What intervention features (i.e. BCTs and PSD principles) are associated with an increase in user engagement within self-guided DBCI's?

Methodology

Rapid Review

Within the field of health technology, rapid reviews have emerged as a frequently used style of review (Sharpe et al., 2017). Currently, there is no agreed upon guidance or methodology for rapid reviews. As rapid reviews are conducted within condensed timelines, they include fewer citations yet follow the main principles of systematic reviews (Sharpe et al., 2017). Due to this, the Cochrane Guidance for Systematic Review was used, following the guidelines when conducting a systematic search and systematic presentation. This was done to reduce selection and information bias present within the review.

Search Strategy

A literature search was conducted throughout May and June of 2020 on the electronic databases PsycINFO and Cochrane Library. Whilst formulating the search terms importance was given to both sensitivity and specificity. The key terms used for the literature searches are displayed in Table 1. Terms were searched for within the titles and abstracts of the literature.

Table 1. Search Terms for PsychINFO

(engagement OR	AND (self-guided OR	AND (digital behav* change OR
user engagement	self-help	digital behav* change intervent*
adoption	prevention	behav* change technolog*
attrition	preventative	ehealth
adherence		mhealth
		persuasive technology

Inclusion and Exclusion Criteria

Research that explored engagement within self-guided DBCIs were searched for. The inclusion and exclusion criteria was determined by using PICOS and the research question. To be included within the review the articles had to be: (1) peer-reviewed; (2) available in English; (3) published in the last five years. The participants had to be: (4) above 18; (5) non-clinical; (6) living in a developed country. The DBCI had to be: (7) aimed at increasing psychological well-being and/or health-related behaviours; (8) digital; (9) self-guided; (10) measure of engagement had to be included. Articles that were narrative or literature reviews were excluded. Interventions that were self-guided but were complementary to therapy were also excluded. Due to demographic barriers to engagement being present, literature was excluded if the research was carried out within a developing country, as the barriers to engagement differ significantly when compared to developed countries (O'Connor et al., 2016). Similarly, studies with participants below 18 were excluded as engagement factors differ between children/teenagers and adults (O'Connor et al., 2016).

Data Collection

The articles identified by the search engines were screened independently by the researcher in two stages. Firstly, by their title and abstract and secondly, the full texts were read. Eligibility of the article was based on the predefined inclusion and exclusion criteria. Any article that the primary researcher was uncertain about was discussed with their supervisor and a joint decision was made in regards to their inclusion.

Data Extraction and Analysis

A data extraction table was used to record key details for the reviewed literature. The data extracted from the citations were coded at 7 levels: (1) Participants; (2) DBCI and Intervention Components; (3) Targeted Behaviour; (4) Study Design; (5) Operationalisation of Engagement; (6) Engagement Outcome; (7) Health Outcomes. The data table was primarily analysed for the relationship between engagement and intervention components.

Results

Search Results and Study Selection

The initial search on PsycINFO and Cochrane resulted in 110 citations. The titles and abstracts were screened using the exclusion and inclusion criteria and 68 were excluded. 42 full papers were examined for eligibility, and nine articles were included in the final analysis. The majority of studies that were excluded in the second round of screening had either guided elements to the intervention, the behaviour targeted was clinical, or they did not operationalise or measure engagement. Although three studies met our inclusion criteria, the intervention studies targeted mental health problems surrounding cancer diagnosis and recurrence. After a discussion with the supervisor, these articles were excluded from the analysis as these mental health problems are more complex, therefore the type of treatment and interventions utilised would differ from more common health concerns.

Design and Characteristics of the Included Studies

Six out of the nine articles included within the review examined a specific intervention and its effect on engagement and health outcomes. Three of the included studies were randomized control trials (RCT). The RCT carried out by Ainsworth et al., (2017) investigated how employment of different intervention features impacted engagement and whether it resulted in increased handwashing amongst users. Mohr et al., (2019) carried out a RCT exploring whether app recommendations influenced engagement and resulted in better depression and anxiety outcomes for the users. Murray, French, Patterson, Kee, Gough, Tang & Hunter (2019) conducted a RCT investigating whether financial incentives promote engagement with an internet-based physical activity intervention.

Vandelanotte et al., (2017) carried out a randomized ecological trial, exploring whether an interactive social physical activity website promoted user engagement and increased physical activity. One experimental study was included by Graham, Jacobs, Cohn, Cha, Abroms, Papandonatos & Whittaker (2020) who carried out a factorial screening experiment, investigating how different intervention features, personalisation, integration, dynamic tailoring and message intensity promotes user engagement and smoking cessation. One study was a qualitative exploration of the facilitators and barriers to engaging with a mindfulness-based intervention amongst healthcare employees (Banerjee, Cavanagh & Strauss, 2017). Two studies conducted a systematic review. Elaheebocus, Weal, Morrison & Yardley (2018) examined whether the inclusion of peer-based social media features increased engagement with interventions. Carolan, Harris & Cavanagh (2017) conducted a systematic review and meta-analysis of 21 RCTs, investigating intervention components that led to better engagement and work-related mental health outcomes. There was one meta-analysis, examining the predictors of engagement with ehealth interventions (Baumel & Kane, 2018).

Targeted Behaviour

The included citations examined DBCI's that targeted a variety of different behaviours. Elaheebocus et al., (2018) and Baumel & Kane (2018) reviewed studies focusing on the main health behaviours, including addiction (alcohol consumption and smoking), diet and nutrition, and physical activity. Other studies focused on a single health behaviour, with physical activity being the most frequently addressed (Murray et al., 2019; Sharpe et al., 2017; Vandelanotte et al., 2017), followed by smoking cessation (Graham et al., 2020), and hand washing (Ainsworth et al., 2017). Mental health was also addressed. Both Carlan et al., (2017) and Banerjee et al., (2017) examined interventions addressing stress, depression and anxiety. Mohr et al., (2019) focused on anxiety and depression. None of the behaviours targeted were clinical in nature that would require a physician or medical assistance.

Intervention Characteristics

An in depth overview of the targeted behaviour, intervention delivery platform and components for each article is presented within Table A1 and can be found in the Appendix (A). The Health Behaviour Theories, BCT and PSD principles implemented within each intervention is summarised in Table 1 below. Only the six studies out of the nine that examined specific interventions were included in Table 1. The table was created utilising the information provided within each article. It is important to note that Banerjee et al., (2017) provided no information in regards to what specific BCT or PSD principles they implemented within their mindful intervention. In regards to the use of social support, four interventions utilised social networking within their intervention, however which social support PSD principles they utilised was not stated in any of the articles (Graham et al., 2020; Mohr et al., 2019; Murray et al., 2019; Vandelanotte et al., 2017).

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Intervention Characteristics

The Health Behaviour Theories, BCT and PSD principles implemented within each intervention is summarised in Table 2 below. Only the six studies out of the nine that examined specific interventions were included in Table 2. The table was created utilising the information provided within each article. It is important to note that Banerjee et al., (2017) provided no information in regards to what specific BCT or PSD principles they implemented within their mindful intervention. In regards to the use of social support, four interventions utilised social networking within their intervention, however which social support PSD principles they utilised was not stated in any of the articles (Graham et al., 2020; Mohr et al., 2019; Murray et al., 2019; Vandelanotte et al., 2017).

Targeted Behaviour

Table 2. Health Behaviour Theories, Behaviour Change Techniques and Persuasive System Design Principles utilised within the Intervention

	Ainsworth et al., 2017	Mohr et al., 2019	Vandelanotte et al., 2017	Graham et al. 2020	Murray et al. 2019	Banerjee et al. 2017
Health Behaviour Theories						
Theory of Planned Behaviour	x					
Social Cognitive Theory				x		
Mindfulness-based stress reduction						x
Mindfulness-based cognitive therapy						x
Behaviour Change Techniques						
Provide information about health link	x		x	x	x	
Provide information on consequences	x		x	x	x	
Prompt intention formation	x					
Prompt specific goal setting	x	x		x	x	
Prompt review of behavioural goals		x				
Prompt self-monitoring of behaviour	x		x	x	x	
Provide feedback on performance					x	
Provide contingent rewards					x	

Teach to use prompts or cues				x	
Prompt practice		x			x
Use follow up prompts					
Plan social support or social change		x	x	x	x
Prompt identification of role model				x	
Relapse prevention				x	
Motivational intervention	x				
Time management		x			
Persuasive System Design Principles					
Reduction		x			
Tunneling		x			
Tailoring	x			x	
Personalisation	x	x	x	x	
Self-monitoring	x		x	x	x
Praise					
Rewards					x
Reminders		x			
Suggestions		x			
Expertise	x				

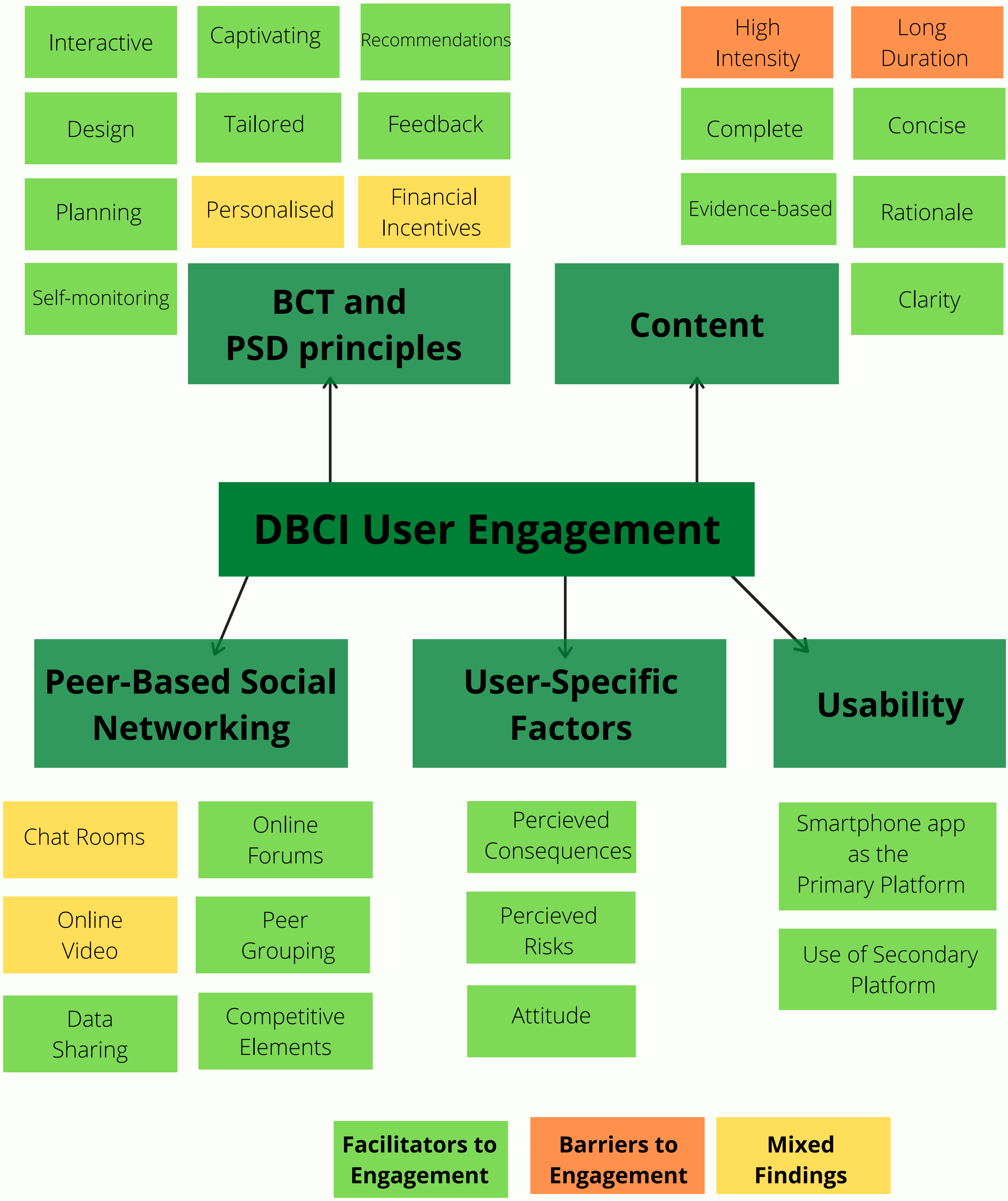
Operationalisation of Engagement

The entirety of the literature included within the review operationalised engagement from a behavioural approach, however the definition and complexity of their measures differed greatly, with no study utilizing the same definition of DBCI engagement. All articles utilised usage measures that were recorded and drawn from the digital intervention platform. Three studies utilised one measure of engagement, measuring the number of sessions completed (Ainsworth et al., 2017), percentage of participants that completed all parts of the intervention (Carolan et al., 2017) and the usage of the website (Banerjee et al., 2017). The researchers of the meta-analyses defined engagement broadly, with either no specific definition of engagement (Elaheebocus et al., 2018), or operationalising engagement as the average app usage time and user retention after 30 days (Baumel & Kane, 2018). The remaining four studies operationalised engagement more specifically, pertaining to particular usage behaviour. Mohr et al., (2019) operationalised engagement as the time to last use, number of app sessions and number of apps downloaded. Vandelanotte et al., (2017) defined engagement specifically to the use of their intervention features as the total and average number of days with a step count entry, step count comments and the time between the first and last step entry. Murray et al., (2019) operationalised engagement as the percentage of days during which participants walked for at least 10 minutes, percentage of weeks in which the participants logged onto the website, percentage of earned points redeemed over the intervention periods, and frequency of hits on each intervention component for every 10 days the participant accessed the website. Graham et al., (2010) measured engagement through page views, time on site, return visits to the website and the use of the six interactive features of the intervention.

Engagement and Health Outcomes

The reviewed literature identified an array of intervention- and user specific factors that facilitated or hindered user engagement. A model summarising the facilitators and barriers of engagement can be seen within Figure 2. The barriers are indicated in orange, the facilitators are in green and the mixed findings are in yellow.

Fig 2. Model summarising the Facilitators and Barriers to Engagement



Intervention Factors

Rationale and Evidence-Based Content.

The content of the intervention and whether it is evidence-based was found to be positively related to the real-life usage of the app (Baumel & Kane, 2018). It is important for the user to understand how the intervention works and how it addresses their behavioural concerns (Banerjee et al., 2017). If the rationale of the intervention is not clear it is a barrier to user engagement. Whereas the support of promising research findings and interventions that are evidence-based facilitate engagement (Banjeree et al., 2017).

Time, Duration and Intensity.

The importance of time was found to be significant in regard to the session length (Mohr et al., 2019), as well as the intervention length (Carolan et al., 2019). An intervention session shorter than 30 seconds (Mohr et al., 2019) and an intervention the length of six to seven weeks (Carolan et al., 2017) was found to be the most effective in regards to engagement. If the intervention is perceived as being too demanding and time intensive it contributes to user disengagement (Banerjee et al., 2017). The more seamlessly the intervention fits into the users day, the more easily it can become a habit for the user. Habit formation increases engagement with the intervention as well as the targeted behaviour, such as physical exercise and mindfulness (Banerjee et al., 2017; Murray et al., 2019). When utilising text messaging in addition to the primary intervention, the intensity (frequency) of the automated text messages had no impact on user engagement (Graham et al., 2020).

Primary and Secondary Platform and Integration.

Phone apps have higher engagement rates than websites or computer based platforms (Carolan et al. 2017). In addition to the primary platform, employing another digital platform such as automated text messaging, and integrating the two platforms effectively, facilitates engagement (Graham et al., 2020).

Usability.

High usability of an app was not significantly associated with higher user engagement (Baumel & Kane, 2018). However, if an app is not user friendly it is a significant barrier to engagement (Baumel & Kane, 2018). Murray et al., (2019) found that technological and usage issues within an intervention have both negative outcomes on engagement as well as the intervention-targeted behaviour.

Behaviour Change Techniques and Persuasive System Design.

The design and layout of the app was found to be a facilitator to user engagement (Baumel & Kane, 2018; Mohr et al., 2019). Previous research on app usage found that app users use a variety of apps for different purposes and that they mostly use apps for a short period of time; Mohr et al., (2019) designed their digital health intervention to reflect how users commonly utilise smartphone apps. The intervention consisted of twelve separate apps, requiring maximum 30 seconds. This design reduced complex behaviours to simple and more manageable tasks (reduction) and increased user engagement, with 84% of participants continuing to use the app after completion of the 8 week treatment (Mohr et al., 2019). They concluded that the novelty that comes with each new app download and use, as well as the limited time spent on the app, contributed to the increased engagement.

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Baumel & Kane (2018) found that interventions which utilised persuasive design elements were high in user engagement. Specifically, interventions that are captivating, interactive, not irritating, targeted, as well as tailored and personalised facilitate engagement (Baumel & Kane, 2018). Tailored and personalised content was consistently found to increase user engagement as well as increase intervention-targeted behaviour such as handwashing (Ainsworth et al., 2017), reduction in stress, depression, anxiety (Carolan et al., 2017) and smoking cessation (Graham et al., 2020). However, in regards to personalisation, simply using the user's name when the content is generic does not enhance engagement (Graham et al., 2020). Carolan et al., (2017) found that feedback and self-monitoring were the most frequently used intervention components, and the higher frequency of use was associated with a significant increase in physical activity at 6 months. Self-monitoring also contributed to increased hand washing after one session (Ainsworth et al, 2017). The recommendation of the app, or the next component of the intervention, significantly increased how many intervention sessions the user finished (Mohr et al., 2019) Recommendations correlated with greater depression improvements amongst users, however had no effect on anxiety outcomes (Mohr et al., 2019). Planning also increased user engagement and increased the performance of the targeted behaviour (Ainsworth et al., 2017; Murray et al. 2019). Action planning, such as planning walking routes for physical activity, lead to significant more steps and higher engagement among users (Murray et al., 2019). Similarly interactive digital plans and If-then plans effectively aided the user in engaging in hand-washing (Ainsworth et al., 2017). Other BCTs such as positive reinforcement through financial incentives did not impact user engagement (Murray et al., 2019).

Peer-Based Social Networking.

The inclusion of social networking features within a digital intervention was found to largely facilitate user engagement within health interventions, with participants spending more time using the intervention (Elaheebocus et al., 2018). The majority (70%) of interventions that included elements of social networking had a significantly positive effect on the users health behaviours, 28% had a neutral outcome and 2% had a negative outcome (Elaheebocus et al., 2018). Features from the communication category, such as online forums, were found to support engagement over longer periods of time. However, interventions that included synchronous features, such as online video and chat rooms reported no significant effect or even reduced engagement. The inclusion of peer grouping and data sharing significantly increased engagement among females. The ability to form social connections, share activity data and use private groups to share photos and fill out polls motivated users and increased the frequency of intervention visits. Competitive elements, especially within interventions that addressed physical activity promoted engagement, especially for individuals who are competitive. Contrary to Elaheebocus et al's (2018) findings, Graham et al., (2020) found that engagement with social networking features was very low within their intervention and it did not impact engagement with the intervention or the behaviour.

Quantity of Intervention Components.

Whether the number of intervention components employed within an intervention increases user engagement showed mixed results. Graham et al., (2020) found that including dynamic tailoring, personalisation, intensity and integration of automated text messaging and the web based intervention within their intervention resulted in the highest level of engagement. However, Vandelanotte et al., (2017) implemented many intervention features that have shown to be effective in increasing engagement, such as peer-based social networking, self-monitoring, and education resources, yet user engagement remained low. Although engagement rates were higher compared to an intervention that only employed a step log and a resource library, only 6.55% of the participants continued using the app after the 10 weeks intervention. Despite the low engagement rate, the intervention had a positive influence on the users physical activity and significantly reduced the users BMI.

User Factors

Attitude.

The user's attitude towards both the intervention and the targeted behaviour has to be positive, to facilitate engagement (Ainsworth et al., 2017; Banerjee et al., 2017). The user's awareness of the effectiveness of the intervention and belief that it can be successful was found to be the main precursor of the user's willingness to engage in the intervention (Banerjee et al., 2017). A positive attitude also elicits motivation to change behaviour and take part in the intervention (Banerjee et al.,2017).

Perceived Risk.

Ainsworth et al., (2017) found that perceived risk of infection was a key predictor of attitudes and intentions towards both using the app and performing the intervention targeted behaviour, handwashing.

Perceived Consequences.

If the consequences/side-effects of the intervention are perceived as being positive these facilitate engagement. Negative or harmful consequences of engaging with the intervention were found to be disengaging (Banerjee et al., 2017).

Discussion

Research has established that user engagement is essential to effectively promote health behaviour change through the utilisation of DBCIs. User engagement with self-guided DBCIs is influenced by a multitude of factors, and this rapid review aimed to primarily identify the facilitators of engagement. The results revealed that both user- and intervention-specific factors affect engagement. The majority of user specific factors which facilitate engagement surround attitude. Attitude plays an important role in engagement, as it guides the thoughts, behaviour and feelings of a user (Glasman & Albarracin, 2006). The attitude of the users has to be positive for the user to initially engage as well as adhere to the DBCI (Ainsworth et al., 2017; Banjeree et al., 2017). Although changing the attitude of users can be difficult, all of the self-guided interventions within this review employed BCTs and PSD principles to alter the users attitude to increase engagement.

Aligned with previous research findings, our review found that the use of BCTs and PSD principles increased user engagement within self-guided DBCI's (Kelders et al., 2012; Wildeboer, Kelders, & van Gemert-Pijnen, 2016). Through the use of Michie's BCT Taxonomy we identified that the majority of interventions used goal-setting, self-monitoring, planning and social support features which were all associated with increased user engagement (Ainsworth et al., 2017; Carolan et al., 2017; Graham et al., 2020; Mohr et al., 2019; Murray et al., 2019). Goal setting, self-monitoring and planning are all self-regulatory BCT's (Michie, Wood, Johnston, Abraham, Francis & Hardeman, 2015). High levels of self-regulation are strongly tied to the behavioural initiation and behavioural maintenance, with Bauer & Baumeister (2011) arguing that to override, inhibit or alter a dominant response tendency, people must possess a sufficient degree of self-regulation (Rothman, Baldwin, Hertel & Fuglestad, 2011). Therefore, BCT's that aim to foster and improve one's self-regulatory abilities aids the individual to not only continue performing the behaviour but to also engage with the intervention that targets the behaviour change.

In regard to PSD principles all interventions except Banjeree et al., (2017) employed at least two principles from the primary task support group. This is in line with Lehto & Oinas-Kukkonen (2011) research, which concluded that primary task support principles are implemented frequently across digital interventions. Numerous interventions included peer-based social networking components, however no specific persuasive technology element of social support was identified by any researchers. Similar to previous research findings, our review found that primary task support features were the most used principles, and also contributed significantly to increased user engagement (van Gemert-Pijnen, Kelders, Beerlage-de Jong & Oinas-Kukkonen, 2018). Tailored and personalised content was found to aid user engagement throughout numerous interventions (Ainsworth et al., 2017; Carolan et al., 2017; Graham et al., 2020). Tailoring refers to " the provision of information, advice and support that is individualised to the user" (Morrison, 2015). Tailoring is particularly important within the health domain as providing tailored and personalised content provides reassurance to the user that they are receiving content and advice that is relevant to them and their health needs (Morrison, 2015). The Elaboration Likelihood Model (Petty & Cacioppo, 1986) highlighted that tailored and personalised interventions are more successful in changing user's attitude and increasing engagement, through increasing the perceived personal relevance of the intervention content. This directs the attention of the user to only the necessary intervention components, allowing the intervention to be more manageable, thereby decreasing the cognitive load placed on the user (Morrison, 2015). How tailored an intervention is can range from being relatively simple (i.e. inserting a person's name) to very complex (i.e. adapting content presented). The review findings revealed that the complexity of tailoring implemented by the intervention is associated with user engagement. Simply adding the user's name does not significantly engage users (Graham et al., 2020), whereas employing complex and automated algorithms to facilitate automated communication through text messages significantly increased user engagement (Graham et al., 2020). Although the use of complex algorithms is beneficial to self-guided apps, the implementation of these algorithms requires in-depth and time extensive qualitative studies to understand what the target population requires, and how they intend to use the intervention (Morrison, 2015). Due to technological and economic restraints complex tailoring may not be feasible to implement for many interventions, a study by Asbjørnsen et al., (2019) demonstrated that it may not be necessary for all interventions. They found that the simple use of goal setting and system preferences could meet the individual needs of the user and stimulate engagement (Asbjørnsen et al., 2019).

Our review identified that another commonly utilised feature within self-guided apps was peer-based social networking, which employs both BCT (i.e. feedback, social support) and PSD principles (i.e. social facilitation, competition). The professional and the positive impact they have on user engagement is absent within self-guided interventions, therefore self-guided interventions are required to implement alternative intervention features to increase engagement. Peer social networking has the ability to address similar engagement factors as professionals do (i.e. social support, surveillance, motivation (Karekla et al., 2019), and can successfully increase user engagement (Elaheebocus et al., 2018). Social networking enhances the user's perception of social support, which acts as a motivation to adhere to the intervention (Elaheebocus et al., 2018). The community that is established through peer-based social networking is valuable to a self-guided intervention as many users seek social connections and utilise social networking to satisfy their need for social support (Poirer & Cobb, 2012; Chang, Chopra, Zhang & Woolford, 2013). The ability to communicate with others not only provides social support but also social influence, social reinforcement, and accountability, which contribute to behaviour change (Poirier & Cobb, 2012). The most effective and frequently used social networking features within digital interventions are the ones that facilitate communication.

Communication can occur many-to-many, one-to-one and one way. In particular, online forums, which facilitates many-to-many communication, increased the usage of the intervention and motivated the majority of the participants to adhere to their intervention and behavioural goals (Elaheebocus et al., 2018). Peer grouping and data sharing also motivated participants to engage more actively with an intervention (Elaheebocus et al., 2018).

The relationship between the number of PSD principles and/or BCTs employed and the intervention effectiveness has been previously investigated and the findings were mixed (van Gemert-Pijnen et al., 2018). Gemert-Pijinen et al., 2018 concluded that the number of intervention components included has the capacity to contribute to engagement in certain scenarios (van Gemert-Pijnen et al., 2018). Similarly, our review found that the implementation of multiple intervention components can sometimes increase engagement (Graham et al., 2020). However, there is no linear relationship between the number of BCTs and PSD principles implemented and user engagement, as the relationship is more complex. Rather, it is the combination of features that is associated with user engagement (Wildeborer et al., 2016; Graham et al., 2020). Components that supplement one another, have the ability to strengthen their effect (van Gemert-Pijnen et al., 2018). Graham et al. (2020) found that dynamic tailoring, personalisation, intensity and the integration between their two platforms (website and automated text messaging) led to the highest form of engagement within their study. These results demonstrated that these four features work together effectively to enhance user engagement. Components that are coupled together with low synergy, tend to be ineffective (van Gemert-Pijnen et al., 2018). To determine which intervention components and features fit together best, more research has to be conducted (van Gemert-Pijnen et al., 2018).

In sum, our findings suggest that BCT and PSD principles are effective in increasing user engagement. Acknowledging the significant impact attitude has on behaviour change demonstrates why BCTs and PSD principles can, if implemented correctly, effectively increase engagement, as their principles center around changing the users attitude. However, there are some considerations that have to be taken into account when implementing these features within DBCI's. Firstly, not all users may have the same preferences for BCT and PSD principles. Elaheebocus et al. (2018) found that significantly more females than males engage in the online use of social networking, and Carolan et al., (2017) concluded that the use of social networking is very trait-specific, finding that not all users seek engagement. It is important to acknowledge that not all BCTs and PSD principles are universally effective in increasing engagement and may even adversely impact the usage of some individuals (Elaheebocus et al., 2018; Mohr et al., 2017). Secondly, the impact of the BCT and PSD principles is dependent on the type of health behaviour the intervention addresses (Zemin, & Keeling, 2010). For instance, symptoms of depression include loss of motivation and isolation, therefore social networking, which requires active participation of the users to be effective, may have limited success in increasing engagement for individuals with depressive symptoms (Elaheebocus et al., 2018). Therefore, when choosing what features to include within the intervention DeSmet, De Bourdeaudhuij, Chastin, Crombez, Maddison & Cardon (2019), recommended the use of user-centered designs during the initial design and creation of interventions. Thirdly, effective implementation of PSD principles, such as personalisation and tailoring requires advanced technology and algorithms, such as Artificial Intelligence and/or Machine Learning, which are costly and may not be easily implemented by every intervention.

Limitations

This rapid review has several limitations. The complexity and multi-dimensionality of engagement was not operationalised or addressed by any of the included literature. All of the included literature only defined user engagement in behavioural terms, therefore the cognitive and emotional measures of engagement user were not addressed. This limited approach does not allow for the review findings to be generalised beyond behavioural engagement. Additionally, none of the literature examined the effect of different factors on the various stages of engagement. For instance, some factors may play a more important role in the initial point of engagement but may not be important in long term engagement, however this differentiation and insight was never made. Future research should utilise a more holistic approach to studying engagement, operationalising engagement in a multi-faceted way, and the complexity and timeline of engagement should be considered.

The studies included lacked ecological validity and the findings may not reflect the real world usage of the apps. The additional motivators and incentives that accompany participating within research may affect their engagement levels with intervention. Vandelanotte et al., (2017) found that engagement within an ecological trial was significantly lower than compared with a RCT. Through this finding it can be inferred that some of the engagement that the users showed was due to the research environment, and that the implementation of the intervention features studied may have a differing impact on 'real life' users.

Lastly, not all BCTs and PSD principles utilised within an intervention were made known to the reader within the articles. Ainsworth et al., (2017) intervention incorporated 18 BCTs which were not all identified. Similarly, Banjeree et al., (2017) provided no information in regards to what intervention components were utilised.

The lack of clarity and information surrounding the intervention components affects the findings of the research as it is not certain which combination of intervention features aided user engagement. The BCT Taxonomy and PSD Model were created in part to aid research and make the intervention features used more transparent and identifiable. Future research should make it more explicit which intervention features are included, even if not all will be actively examined by the researcher.

Conclusion

The results of the review indicate that both intervention and user specific factors influence engagement. The user specific factors that impact engagement were attitude, perceived risk and perceived consequences. Some of the user specific factors, such as perceived risk of using DBCIs and attitude towards DBCIs are difficult to change, and usually require environmental agents at both societal and political level. By enhancing the acceptance and effectiveness of digital health interventions, as well as the importance of taking preventative measures against the development of serious mental and physical health problems at a societal level (i.e. marketing campaigns and policies), user engagement with DBCI's could be enhanced. For creators and businesses of DBCIs targeting the user specific factors that influence engagement may be mostly out of reach. What is more accessible and feasible is creating interventions that utilise engaging intervention features. The rapid review results highlight that the content of the intervention, the BCTS and PSD principles included and the usability of the intervention all play a significant role in facilitating user engagement, if implemented and used correctly.

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