

Attrition in conversational agent delivered mental health interventions: A systematic review and meta-analysis

Ahmad Ishqi Jabir, Xiaowen Lin, Laura Martinengo, Gemma Sharp, Yin-Leng Theng, Lorainne Tudor Car

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Attrition in conversational agent delivered mental health interventions: A systematic review and meta-analysis

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Abstract

Background: Mental health disorders are widespread, but access to evidence-based mental health interventions is limited. Conversational agents (CAs) or chatbots are computer programs that mimic human conversation. They have the potential to improve access to mental health interventions through automated, scalable, and personalized delivery of psychotherapeutic content through a human-like interaction. However, digital health interventions, including those delivered by CAs, often have high attrition rates. Identifying the factors associated with attrition is critical to improving future clinical trials and leveraging the potential of these interventions.

Objective: This review aimed to estimate the overall and differential rates of attrition in CA-delivered mental health interventions, evaluate the impact of study design and intervention-related aspects on attrition, and describe study design features aimed at reducing or mitigating study attrition.

Methods: Systematic review and meta-analyses of overall and differential attrition of CA-delivered mental health intervention RCTs was conducted in June 2022. Five databases were searched, and a grey literature search was also conducted. We included randomized-controlled trials (RCTs) that compared CA-delivered mental health intervention against control groups and excluded studies that lasted for one session only and used "Wizard-of-Oz" interventions. We also assessed the risk of bias in the included studies using Risk-of-Bias Tool 2.0. Random-effects proportional meta-analysis was applied to calculate the pooled dropout rates in intervention groups. Random-effects meta-analysis was used to compare the attrition in the intervention compared to control groups. We used a narrative review to summarize the findings.

Results: The systematic search retrieved 5,197 records from peer-reviewed databases and citation searches and 41 RCTs met the inclusion criteria. The mean meta-analytic overall attrition rate in the intervention group was 21.84% (95% CI [16.74, 27.36]), I² = 94%. Short-term studies that lasted 8 weeks or shorter showed a lower attrition rate at 18.05% (95% CI [9.91, 27.76]), I² = 94.6, compared to long-term studies that lasted more than 8 weeks, 26.59% (95% CI [20.09, 33.63]), I² = 93.89. Intervention group participants were more likely to attrit compared to control group participants for short-term, log OR = 1.22 (95% CI [0.99, 1.50]), I² = 21.89%, and long-term studies, log OR = 1.33 (95% CI [1.08, 1.65]), I² = 49.43%. Intervention-related characteristics associated with higher attrition include stand-alone CA intervention without human support, not having a symptoms tracker feature, no visual representation of the CA, and comparing CA intervention with wait-list controls. No participant-level factor reliably predicted attrition.

Conclusions: Our results indicated that about one-fifth of the participants will drop out from CA-delivered interventions for short-term studies. This was comparable to face-to-face mental health intervention and less than most digital health interventions based on other meta-analyses. However, there were high heterogeneities which made it difficult to generalize the findings. Our

results suggested that future CA-delivered mental health interventions should adopt a blended design with human support, use symptom tracking, compare CA interventions against active controls rather than wait-list, and include a visual representation of the CA to reduce the attrition rate. Clinical Trial: CRD42022341415

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Original Manuscript

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Keywords	conversational agent; chatbot; mental health; mHealth; attrition; mobile health

Abstract

Background: Mental health disorders are widespread, but access to evidence-based mental health interventions is limited. Conversational agents (CAs) or chatbots are computer programs that mimic human conversation. They have the potential to improve access to mental health interventions through automated, scalable, and personalised delivery of psychotherapeutic content through a human-like interaction. However, digital health interventions, including those delivered by CAs, often have high attrition rates. Identifying the factors associated with attrition is critical to improving future clinical trials and leveraging the potential of these interventions.

Aim: This review aimed to estimate the overall and differential rates of attrition in CA-delivered mental health interventions, evaluate the impact of study design and intervention-related aspects on attrition, and describe study design features aimed at reducing or mitigating study attrition.

Methods: Systematic review and meta-analyses of overall and differential attrition of CA-delivered mental health intervention RCTs were conducted in June 2022. We searched PubMed, EMBASE (Ovid), PsychINFO (Ovid), Cochrane Central Register of Controlled Trials, and Web of Science as well as grey literature search on Google Scholar. We included randomized-controlled trials (RCTs) that compared CA-delivered mental health intervention against control groups and excluded studies that lasted for one session only and used “Wizard-of-Oz” interventions. We also assessed the risk of bias in the included studies using Risk-of-Bias Tool 2.0. Random-effects proportional meta-analysis was applied to calculate the pooled dropout rates in intervention groups. Random-effects meta-analysis was used to compare the attrition in the intervention compared to control groups. We used a narrative review to summarize the findings.

Results: The systematic search retrieved 5,197 records from peer-reviewed databases and citation searches and 41 RCTs met the inclusion criteria. The mean meta-analytic overall attrition rate in the intervention group was 21.84% (95% CI [16.74, 27.36]), $I^2 = 94\%$. Short-term studies that lasted 8 weeks or shorter showed a lower attrition rate at 18.05% (95% CI [9.91, 27.76]), $I^2 = 94.6\%$, compared to long-term studies that lasted more than 8 weeks, 26.59% (95% CI [20.09, 33.63]), $I^2 = 93.89\%$. Intervention group participants were more likely to attrit compared to control group participants for short-term, log OR = 1.22 (95% CI [0.99, 1.50]), $I^2 = 21.89\%$, and long-term studies, log OR = 1.33 (95% CI [1.08, 1.65]), $I^2 = 49.43\%$. Intervention-related characteristics associated with higher attrition include stand-alone CA intervention without human support, not having a symptoms tracker feature, no visual representation of the CA, and comparing CA intervention with wait-list controls. No participant-level factor reliably predicted attrition.

Conclusion: Our results indicated that about one-fifth of the participants will drop out from CA-delivered interventions for short-term studies. This was comparable to face-to-face mental health intervention and less than most digital health interventions based on other meta-analyses. However, high heterogeneities made it difficult to generalize the findings. Our results suggested that future CA-delivered mental health interventions should adopt a blended design with human support, use symptom tracking, compare CA interventions against active controls rather than wait-list, and include a visual representation of the CA to reduce the attrition rate.

Attrition in conversational agent delivered mental health interventions: A systematic review and meta-analysis

Background

Description of the problem

Mental health disorders are one of the largest contributors to the global disease burden affecting one in every eight people or 970 million people around the world [1,2]. However, access to evidence-based interventions for the prevention and treatment of mental health disorders is limited [3,4]. This is due to various factors such as a lack of mental health services and professionals, poor mental health literacy, fear of stigma and low perceived need for treatment [5–10]. There is a need for scalable and accessible mental health services. Digital technologies such as smartphones or websites are increasingly used for the delivery of mental health interventions and have the potential to improve access to mental health care. Digital mental health interventions allow for scalable delivery of diverse therapeutic approaches such as cognitive-behavioral therapy and mindfulness for the treatment of mental health conditions such as depression, anxiety, substance abuse, and eating disorders [11–13].

Description of the intervention

Conversational agents (CAs) or chatbots are a more recent type of digital intervention which are becoming a popular channel for mental health interventions delivery. CAs can be defined as computer algorithms designed to simulate human conversations textually or via speech through an interactive interface [17]. CA-delivered interventions combine the delivery of psychotherapeutic content with an automated dialogue system which simulates the interaction between a mental health expert and the user [18]. These interventions provide an alternative avenue of psychotherapy to individuals who are not able to access mental health services due to time, location, or availability of resources [19]. CAs can also be a useful addition to traditional in-person therapy [20,21]. The presence of CA can further contribute to improved therapeutic alliances with users to enhance adherence to the intervention [22,23]. Evidence for the efficacy of CAs in delivering mental health support is growing steadily. A recent meta-analysis showed that CA-delivered psychotherapy in adults significantly improved depressive symptoms with a medium effect size [19]. Providing self-guided therapy remotely via CAs may help address barriers to mental health access such as cost, long waiting time, and stigma [29]. While the impact of mental health interventions delivered by CAs seems promising, studies evaluating such interventions also suggest high study attrition among participants [19]. Attrition or dropout occurs when participants do not complete the randomised clinical trial assessments or complete the research protocol.

Digital health interventions typically reported rapid and high attrition [13]. The overall attrition quantifies the level of attrition for the whole sample in a clinical trial and the differential attrition refers to the level of attrition in the intervention group relative to the comparison group [31]. Attrition in clinical trials may introduce bias by modifying the random composition of the trial groups, limiting the generalizability of the study, and reducing the study power due to reduced sample size [13,32]. To improve the quality of future clinical trials on CA-delivered mental health interventions, there is a need to determine the attrition rate and the factors contributing to the attrition in CA-delivered interventions.

Why is it important to do this review?

There is scant evidence on the possible factors associated with attrition in CA-delivered interventions for mental health and healthcare in general. The review conducted by Lim et al [19] on the

effectiveness of CA-delivered interventions for depression and anxiety symptoms indicated that almost a fifth of the participants (19%) attrited throughout the trials without exploring factors associated with the attrition. This was comparable to other reviews on digital health mental health interventions reporting attrition rates which ranged from 24.1% to 47.8% after adjusting for publication bias [13,33]. Factors shown to be associated with attrition in trials of digital health interventions, in general, include poor user experience, lack of perceived value, and privacy concerns [33,34]. For example, mental health apps in research reported technical issues and errors which might affect users' overall experience [15,35]. Qualitative findings further suggested that factors such as lack of human interactions in digital health interventions and users' technological competence also played a role in participants' attrition [36].

Additionally, for smartphone-based mental health interventions, providing monetary compensation and reminders to engage were associated with significantly lower attrition rates [13]. Conversely, participants in the intervention condition were more likely to drop out relative to the waitlist [13,37]. These reviews focused on all smartphone-delivered interventions and included studies published before 2020, omitting several more recently published studies on CA-delivered mental health interventions. To fully harness CA-delivered mental health interventions, there is a need to better understand the factors associated with both overall attrition as well as differential attrition in these interventions.

To this end, we aimed to: (a) estimate the overall and differential rates of attrition in CA-delivered mental health interventions; (b) evaluate the impact of the study on design-related and intervention-related aspects on the overall and differential attrition rate in CA-delivered mental health interventions; and (c) map and describe study design features aimed at reducing or mitigating study attrition in the trials.

Methods

We performed a systematic review of attrition rates in randomised controlled trials of CA-delivered mental health interventions in line with the Cochrane gold standard methodology [38] and the meta-analysis approach outlined by Linardon and Fuller-Tyszkiewicz [13]. We reported this review in line with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) reporting guidelines [39]. The protocol for this systematic review was registered with PROSPERO on 1st Aug 2022 (Registration ID: CRD42022341415).

Criteria for studies selection

Type of studies

Our inclusion criteria included randomized control trials (RCT), cluster RCTs, cross-over RCTs, quasi-RCTs, and pilot RCTs in English. We decided to include these variations of RCTs as the field is still nascent and findings from different forms of RCTs could be beneficial to understand the attrition rate in conversational agent delivered mental health interventions. The publication type included peer-reviewed journals and conference papers that were published up to June 2022.

Type of participants

Participants' characteristics included healthy participants and participants with subclinical or clinically diagnosed mental health disorders such as depression, anxiety, attention-deficit/hyperactivity disorder, and bipolar disorder. Participants of any age were included so long as they personally interacted with the CA.

Type of intervention

We included studies reporting a synchronous two-way exchange with the participants via a CA. We excluded studies where the CA dialogues were wholly or partially delivered by human operators

(“Wizard of Oz”) or studies with asynchronous response systems.

The interventions included either the delivery of psychotherapeutic content or provided training to improve mental well-being or reduced symptoms of mental health conditions or both. This included studies that aimed to reduce symptoms of depression for clinical and subclinical populations or studies implementing mindfulness training for healthy adults. Detailed inclusion and exclusion criteria are outlined in Multimedia Appendix 1.

Types of outcome measures

The primary outcome was the reported attrition number and the attrition rate calculated by the weighted risk of attrition of participants against the sample size of the studies for participants assigned to the CA intervention who then discontinued the study. This included the total attrition and differential attrition in the intervention and comparison groups.

Search methods for identification of studies

The search strategy included index terms and keywords that describe CA such as “conversational agent”, “embodied conversational agent”, “virtual assistant”, and “virtual coach” (Multimedia Appendix 2). The search strategy was previously developed for our scoping reviews [40,41] and was updated to include studies from 2020-2022 with the assistance of a medical librarian. We conducted the searches on the following databases on 6th June 2022: PubMed, EMBASE (Ovid), PsychINFO (Ovid), Cochrane Central Register of Controlled Trials, and Web of Science. Additionally, we conducted a grey literature search on the first 200 entries from Google Scholar as suggested by the literature for the most optimal combination of databases [42,43]. We did not include any filter terms in the search. We also performed citation chasing by searching for all records citing one or more of the included studies (forward citation chasing) and all records referenced in the included studies using *Citationchaser* [44]. The table of excluded study is included in Multimedia Appendix 6.

Data collection and analysis

Selection of studies

On updating the searches from 2020 to 2022, we imported all identified references from the different electronic databases into a single file. The duplicated records were removed using *revtool* on R [45] and manually on Zotero. One reviewer (AIJ) performed the title and abstract screening using ASReview [46], an open-source machine-learning software. The software utilizes an active learning algorithm to actively sort and resort the records by prioritizing the most relevant records first based on the user’s inclusion and exclusion decisions. The detailed title and abstract screening steps are detailed in Multimedia Appendix 1.

Three reviewers (AIJ, XL and LM) were engaged for the full-text review. One reviewer (AIJ) retrieved the full text of the studies, and the two reviewers (AIJ and XL) assessed their eligibility independently and in parallel. The disagreements were discussed and resolved between the reviewers and with a third reviewer (LM) acting as the arbiter. Studies that were identified in our previous reviews (up to 2020) [41] and fit the inclusion criteria of this review were included based on discussions between three reviewers (AIJ, XL, and LM).

Data extraction and management

Data were extracted using a data extraction form on Microsoft Excel. The data extraction form was piloted by 2 reviewers (AIJ and XL) on the same 5 papers and amended in line with the feedback. We also included additional fields as required from the data extraction form that we referenced from Linardon and Fuller-Tyszkiewicz [13]. Four reviewers (AIJ, XL, GS, and NF) extracted the data independently and in parallel.

We extracted the year of publication, study design, type of comparison group (active or inactive

comparison group), type of intervention, and details on the CAs including the type of CA (rule-based or AI-enhanced), the personality of the CA [17], level of human support, presence of reminder mechanism and the input and output modalities of the CA. Additionally, we extracted information on the study duration, compensation of study participants and any other mechanism included specifically to increase user engagement. Disagreements between the reviewers were resolved by discussion.

Assessment of risk of bias in included studies

Four reviewers (AIJ, XL, GS, and NF) independently assessed the risk of bias in the included studies using Cochrane's Risk of Bias Tool version 2.0 [38] and visualized using *robvis* [47]. The risk of bias assessment was piloted with 10 studies for consistency and clarity of judgement by two reviewers (AIJ and XL). The detailed steps to the assessment of the risk of bias are detailed in Multimedia Appendix 1. We reported the summary and included the risk of bias table in Multimedia Appendix 3. We requested clarification or more data from one study author and did not receive any response after sending a reminder 2 weeks later. Assessment of publication bias was reported via funnel plot and Egger's test for publication bias [48].

Data analysis

The meta-analysis was conducted based on the approach outlined by Linardon and Fuller-Tyszkiewicz [13] and by the Cochrane Handbook [38]. We defined attrition as the number of participants who dropped out of the study during the intervention period by not completing the post-intervention assessment. We did not include the follow-up period [13]. For crossover design studies, we only included the data before the crossover following the above definition. The second part of the crossover was not considered the follow-up period.

The study's overall attrition was estimated by calculating the weighted pooled event rate using random effect models based on a meta-proportional approach [38] using Freeman-Tukey Double Arcsine Transformed Proportion [49]. This indicated the relative risk of attrition against the sample size of the studies for participants assigned to the CA intervention group. The aim of this overall attrition analysis is to compute the overall rate of attrition in the intervention group after controlling for the different sample sizes in the included studies. Event rates were then converted to percentages of events per 100 participants and calculated separately for all the included studies, short-term studies (≤ 8 weeks from baseline) and longer-term studies (> 8 weeks from baseline). We used short- and long-term groupings to facilitate a comparison between our result and the previous study on attrition in smartphone-delivered interventions for mental health problems [13].

The differential attrition was calculated as the odds ratio of the likelihood to attrit between the CA-delivered intervention compared to the comparison condition. The aim of the differential attrition analysis is to understand the odds of attrition relative to the control group. The odds ratios were calculated using random effect models separately for short-term and long-term studies weighted by their inverse variance. Studies with zero events on both arms were weighted as zero and a correction of 0.5 was added to the arm with zero events as a continuity correction. Log Odds Ratio (log OR) of more than one indicated a higher likelihood of attrition in the CA-delivered interventions compared to the control groups. We also conducted sub-group analyses to explore sources of heterogeneity in both overall and differential meta-analyses. The detailed meta-analysis procedure and sub-group analyses conducted are specified in Multimedia Appendix 1. We also performed post hoc sensitivity analyses for subgroups with less than 5 studies as the estimate of τ^2 might be imprecise [50]. Additionally, we conducted exploratory analyses of all the included studies regardless of the intervention duration using the same set of prespecified sub-group analyses on the overall and differential meta-analyses.

Meta-analysis was not conducted on the participant-level factors and predictors of attrition due to variability in reporting. We also identified additional factors significantly associated with attrition (p

< .05) in the included trials. We collated and narratively presented these factors associated with attrition as reported by the studies.

Results

The updated search strategy retrieved 2,878 records from peer-reviewed databases and 2,319 from citation searching. After removing duplicates, 4,067 were screened on ASReview and 179 were considered for full-text screening. We included 11 studies from the database searches. We further identified two systematic reviews on CA-delivered mental health and included 14 studies that were not identified from our search strategy [19,51]. These studies used the *deprexis* and ePST interventions which did not explicitly identify themselves as CAs. Both *deprexis* and ePST for instance described themselves as simulated dialogue that tailored their responses based on users' input [52,53]. We then followed up with an additional search on PubMed using *deprexis* OR ePST as keywords and included three additional studies ($n = 3$). We also included 13 studies identified in our previous review [41]. The total number of included studies is 41. Figure 1 presents the study selection process.

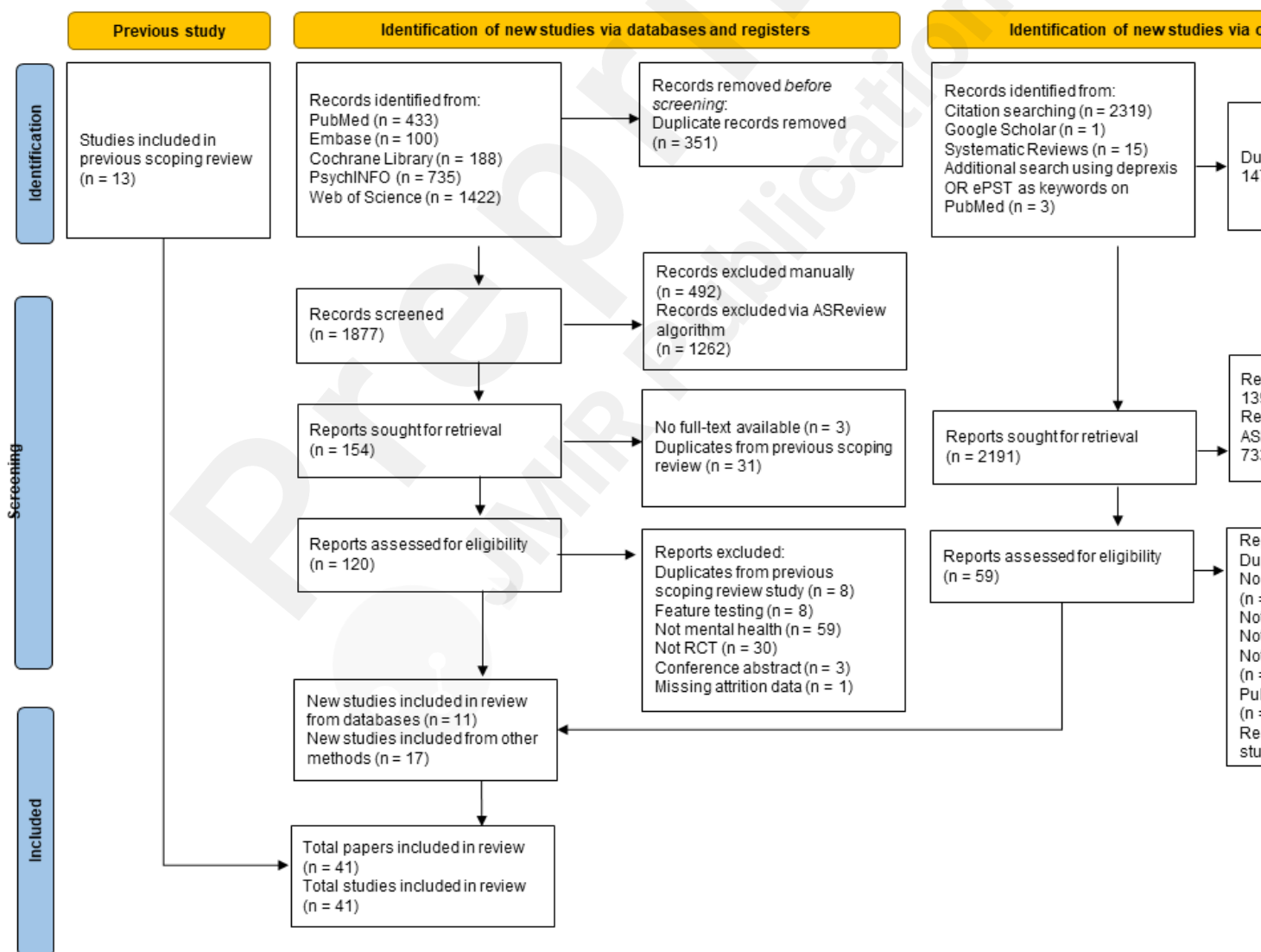


Figure 1: PRISMA flowchart

Table 1. Characteristics of included study.

Study Characteristics		Values, n (%)
Year of publication		
	< 2020	22 (54)
	≥ 2020	19 (46)
Country		
	United States of America	13 (32)
	Germany ^{a, b}	13 (32)
	South Korea	3 (7)
	Switzerland ^{a, b}	2 (5)
	United Kingdom	2 (5)
	Others (European Union) ^{a, c}	5 (12)
	Others ^d	6 (15)
Type of study design		
	RCT	29 (71)
	Pilot RCT	8 (20)
	Crossover RCT	4 (10)
Study Duration		
	≤ 8 weeks	26 (63)
	> 8 weeks	15 (37)
Sample population		
	General population	11 (27)
	At-risk population	18 (44)
	Clinical population	12 (29)
Target clinical outcome		

	Treatment and monitoring	17 (41)
	Education and training	24 (59)
Target disorder/intervention		
	Depression only	17 (41)
	Mental well-being	9 (22)
	Co-occurring depression and anxiety	5 (12)
	Others ^e	10 (24)
Type of control		
	Wait-list control	18 (44)
	Active control	15 (37)
	Treatment as usual	8 (20)
Enrolment method		
	Remote enrolment option only	23 (56)
	In-person enrolment option provided	16 (39)
	Not specified	2 (5)
Session type		
	Defined session length	29 (71)
	User-determined session length	12 (29)
Attrition range		
	0 – 10%	13 (32)
	11 – 20%	6 (15)
	21 – 30%	11 (27)
	31 – 40%	2 (5)
	41 – 50%	3 (7)
	> 50%	6 (15)

^aConducted in both Switzerland and Germany; ^bConducted in Switzerland, Germany, and Austria;

^cIreland, Sweden, Italy, Netherlands; ^dJapan, Ukraine, Argentina, New Zealand, China, Russia; ^eAnxiety only, panic disorder, height phobia, gambling disorder, substance abuse, attention-deficit/hyperactivity disorder, irritable bowel syndrome, eating disorder, personality disorder.

Study characteristics

Of the studies included in this review, 22 studies were published before 2020 (54%) [15,26,52–71] and 19 (46%) were published after 2020 [14,27,72–88] (Table 1). Most of the studies were from the United States of America (13/41, 32%) [14,15,27,53,60,62,63,68,70,71,73,85,88] and Germany (13/41, 32%) [52,54,56–59,64–66,72,78] with some studies conducted in multiple countries such as Switzerland and Germany [55] and Switzerland, Germany, and Austria [61]. Most of the interventions were short-term interventions and lasted eight weeks or less (26/41, 63%) [14,15,26,27,53,56,60,62,66–71,73–77,79–84,87], while 15 studies (37%) lasted more than eight weeks [52,54,55,57–59,61,63–65,72,78,85,86,88].

Psychoeducation and training were the focus of 24 studies (59%) [26,52–61,63–66,68,71–73,78,80–82,87]. Most participants were screened for mental health symptoms before the start of the study (18/41, 44%) [14,27,54,56–60,63,66,67,71,75–77,83,85,86] and enrolled on the study remotely using web or telephone (23/41, 56%) [14,15,26,27,52,54–57,60,61,66,68,70,72,73,75,78,80,84–87]. Most studies focused on depression as the target disorder (17/41, 41%) [52–60,62–66,69,72,86]. Eighteen studies (18/41, 44%) employed wait-list control group participants [14,26,27,53–58,60,62,66,67,71,75,80,81,85], and 15/41 (37%) used an active control which included information or self-help (10/15, 67%) [15,64,70,74,77–79,83,84,86], alternative or comparable treatments such as stress-management CBT without a digital component (3/15, 20%) [76,87,89], or symptoms rating only (2/15, 13%) [68,73].

In the intervention group, 13 studies reported attrition between 0 – 10% [15,26,53,55,62,63,67,70,73,74,76,82,83], 6 studies reported 11 – 20% attrition [14,61,77,81,86,90], 11 studies reported 21 – 30% attrition [52,56,58–60,64,65,71,72,75,88], 2 studies reported 31 – 40% attrition [57,68], 3 studies reported 41 – 50% attrition [27,78,84], and 6 studies reported more than 50% attrition in the intervention group [54,66,79,80,85,87].

Risk of Bias Assessment

The most common risk of bias in the included studies was the bias in the measurement of the outcomes as they were all self-reported outcomes. The second most common bias was due to the selection of the reported results as most of the studies did not cite the RCT protocol or statistical analysis plan. Most of the studies reported intention-to-treat analysis (29/41, 71%). Figure 2 shows the summary plot of the risk of bias.

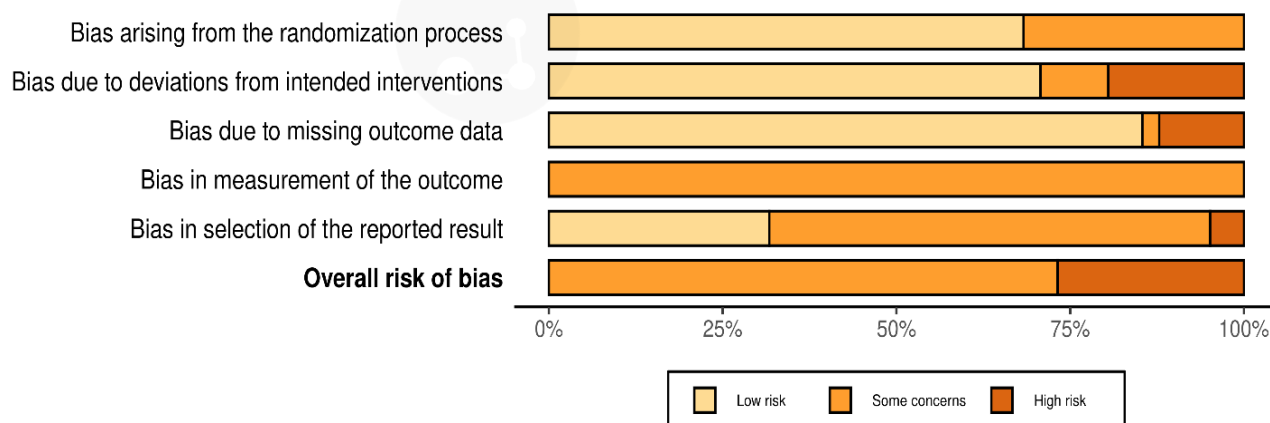


Figure 2: Summary plot for the risk of bias assessment for the included studies.

CA Characteristics

Table 2. CAs characteristics.

CA ^a Characteristics	Values, n (%)
Types of CAs	
No avatar/visual representation	15 (37)
Avatar only	14 (34)
ECA ^b	8 (20)
Not specified	4 (10)
Delivery Channel	
Web-based application	15 (37)
Standalone smartphone app	11 (27)
Computer/Laptop/Tablet embedded program	7 (17)
Messaging app-based ^c	7 (17)
Not specified	1 (2)
Types of CAs Dialogue Modality	
Rule-based	29 (71)
AI-enhanced	12 (29)
CAs' Personality	
Coach-like	19 (46)
Factual	14 (34)
Healthcare professional-like	5 (12)
Informal	3 (7)

^aCA = conversational agent

^bECA = embodied conversational agent

^cSlack, Facebook Messenger, WeChat

Most of the CAs were rule-based (29/41, 71%) and 12 (29%) were AI-enhanced using natural language processing or other AI-based algorithms (29%). Most studies did not describe any specific visual representation of the CA (15/41, 37%). These were mainly studies that included *deprexis* or *deprexis*-based interventions as they did not specifically identify as CAs but used dialogue-based interventions. Fourteen studies included an avatar or a static visual representation of the CAs (34%) and eight studies represented the CA using an embodied conversational agent (ECA). Among the ECAs, most studies used relational agents (4/8, 50%), three studies used 3D-generated renders (3/8, 38%), and two studies used pre-recorded videos (2/8, 25%). The CAs mostly presented a coach-like personality characterised by encouraging and nurturing personalities (19/41, 46%), followed by a factual personality characterised by being non-judgemental and offering responses based on facts and observations (14/41, 34%). Five CAs were designed to look like a doctor or healthcare professional (12%) and three CAs conversed with users using informal language characterised by exclamations, abbreviations, and emoticons in the dialogue (7%). Most of the interventions were delivered via web-based applications (15/41, 37%) followed by a standalone smartphone application (11/41, 27%).

Study Attrition Rates

Overview

The overall weighted attrition rate for the intervention group in all included studies was 21.84% (95% CI [16.74, 27.36]), $I^2 = 94\%$ while the differential attrition differed from zero, log OR = 1.28 (95% CI [1.10, 1.48]), $I^2 = 34.6\%$, indicating the participants who received CA-delivered interventions were more likely to attrit compared to the control group participants. Figure 3 shows

the attrition rates for all the included studies.

Short-term studies (≤ 8 weeks)

In the short-term studies, the overall weighted attrition rate in the intervention groups was 18.05% (95% CI [9.91, 27.76]) and there was evidence of high trial heterogeneity ($I^2 = 94.6\%$, (95% CI [93.05, 95.74])). The high heterogeneity was due to high variations among the studies in terms of symptoms, types of interventions, and study populations. Five studies reported zero attrition in the intervention group [26,53,73,76,89]. The lowest attrition rate was 6.12% (95% CI[1.48, 17.15]) [67] and the highest was 71.05% (95% CI [63.38, 77.69]) [80].

The differential attrition did not differ from zero, log OR = 1.22 (95% CI [0.99, 1.50]) indicating that the attrition rates were similar across the intervention and control groups.

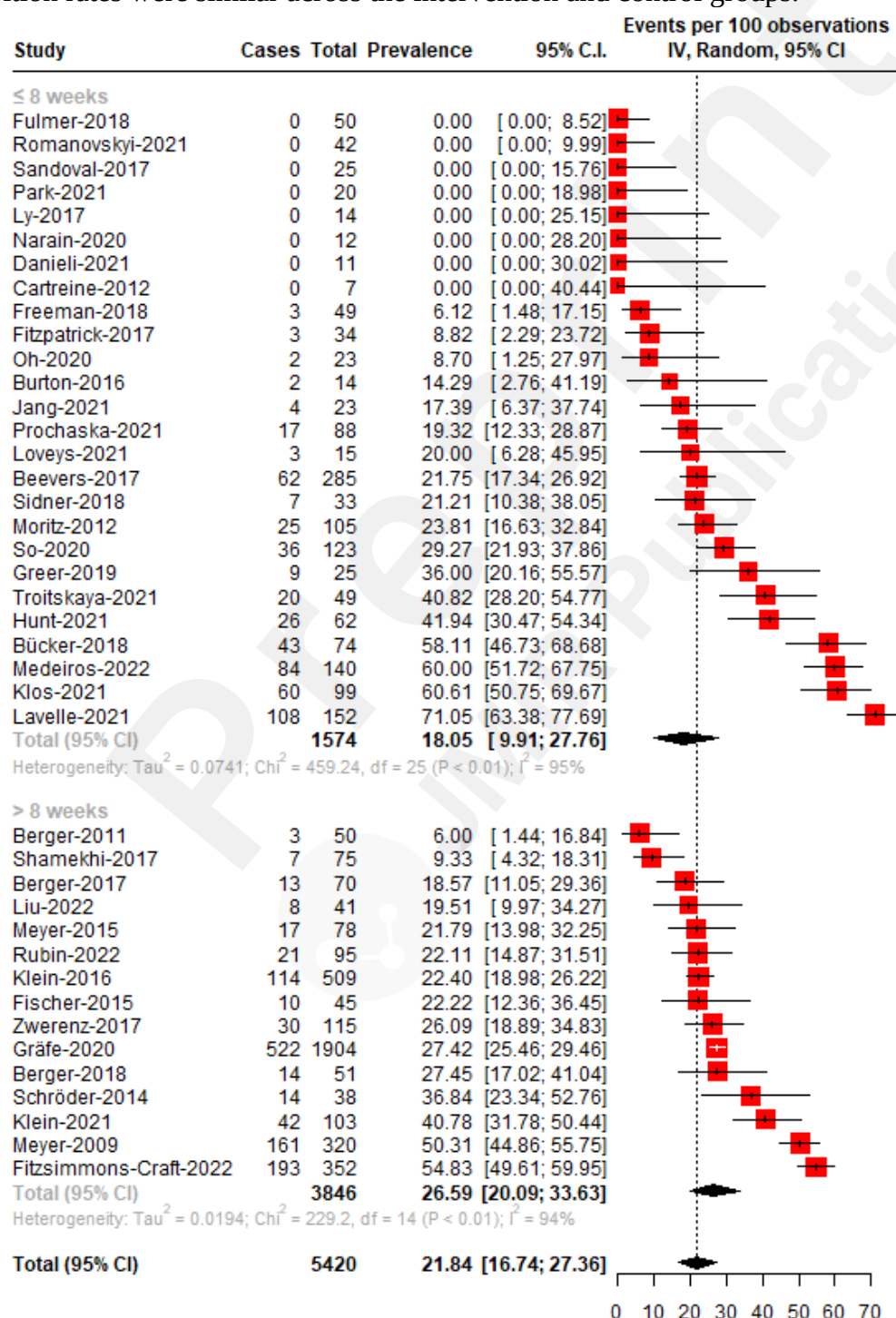


Figure 3: Overall attrition rates for the intervention group in CA-delivered mental health

interventions.

The heterogeneity was low to moderate ($I^2 = 21.89\%$ (95% CI [0.0, 54.60])). One study was identified as a potential outlier [15]. Removing this study from the model improved the I^2 greatly, 1.49% (95% CI [0, 49.68]) and the differential attrition differed from zero, log OR = 1.27 (95% CI [1.04; 1.54]). This indicated that the attrition rate in the intervention group was significantly larger than the control group after removing the outlying study. Multimedia Appendix 4 shows the forest plot for the differential attrition meta-analysis.

Publication bias for short-term studies (≤ 8 weeks)

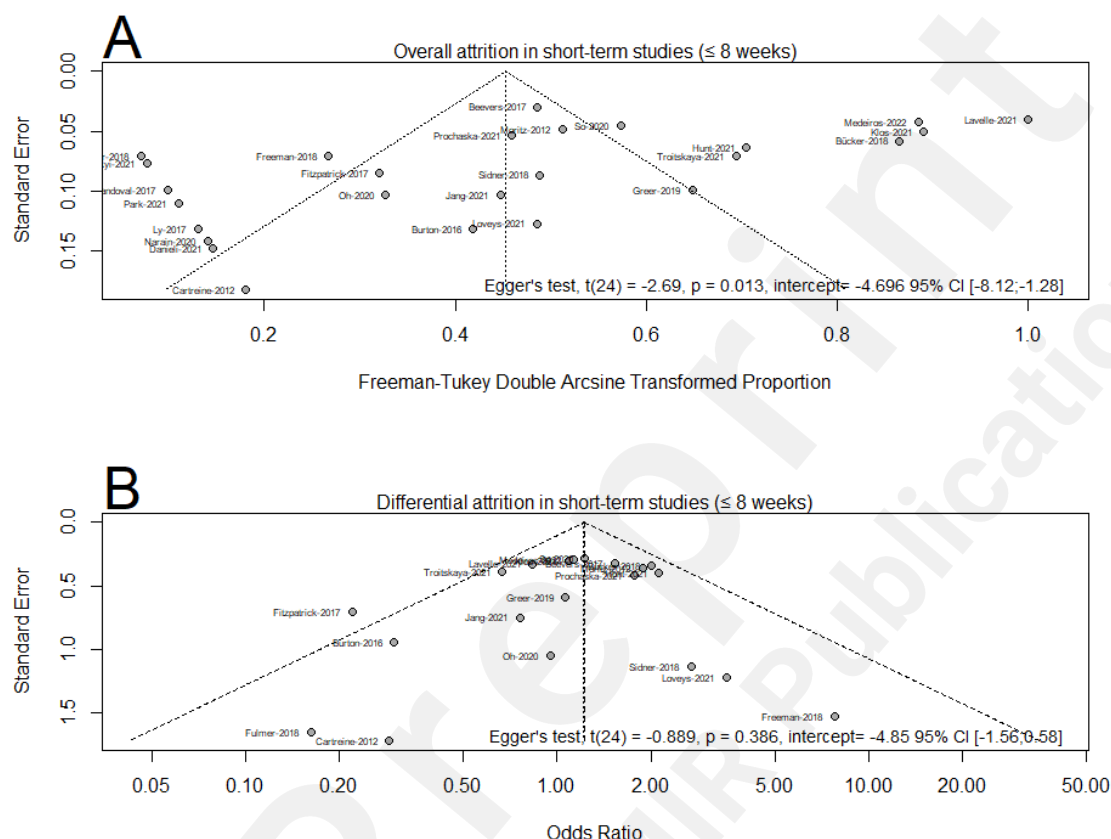


Figure 4. Funnel plots and Egger's test for publication bias for overall attrition (A) and differential attrition (B) in meta-analyses of short-term studies.

For the overall attrition, the Egger's test was significant, intercept = -4.70; 95% CI [-8.12, -1.28]; $p = .013$ indicating possible publication bias. A closer look at the funnel plot showed missing studies on the bottom right of the plot which suggested possible publication bias for small sample-sized studies with high attrition rates (Figure 4A). For the differential attrition, the funnel plot indicated evidence of plot symmetry and the Egger's test was not significant, intercept = -4.85; 95% CI [-1.56, 0.58]; $p = .386$ (Figure 4B).

Subgroup analyses of the attrition rates in short-term studies (≤ 8 weeks)

Subgroup analyses were conducted for both overall (Table 3) and differential attrition (Multimedia Appendix 4) in the CA-intervention group compared to the control.

Table 3. Subgroup analyses for overall attrition in CA-delivered mental health interventions

	Short-term (≤ 8 weeks)	Long-term (> 8 weeks)
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Subgroups		<i>k</i>	Attrition rate, % [95% CI]	<i>I</i> ² (%)	<i>Q</i>	<i>k</i>	Attrition rate, % [95% CI]	<i>I</i> ² (%)	<i>Q</i>
Risk of Bias					0.212				0.22
	High Risk of Bias	8	26.18 [15.69; 38.13]	89.6		4	22.31 [17.85; 27.10]	0	
	Low Risk of Bias	18	14.76 [4.27; 29.25]	95.6		11	28.35 [20.25; 37.20]	95.4	
Funding source					0.705				0.38
	Industry funding	9	20.43 [8.78; 35.06]	92.4		4	32.36 [18.14; 48.46]	97.0	
	Public funding only	17	16.56 [6.35; 29.79]	95.1		11	23.19 [15.92; 33.65]	92.1	
Duration					0.429				0.684
	0-4 weeks	17	15.57 [5.10; 29.92]	95.3					
	5-8 weeks	9	23.15 [11.13; 37.67]	93.4					
	9-12 weeks					11	25.30 [19.35; 31.75]	90.3	
	>13 weeks					4	30.04 [10.75; 53.88]	96.1	
Study Design					0.65				0.192
	RCT ^a	19	19.68 [10.34; 30.95]	95.2		14	26.00 [19.33; 33.27]	94.3	
	Pilot RCT ^a	7	12.73 [0; 38.45]	91.8		1	-	-	
Type of Disorders					0.80				0.319
	Depression	6	17.89 [5.44;34.60]	91.5		11	24.03 [17.74; 30.93]	91.4	

	Depression and Anxiety	5	7.68 [0; 40.93]	97.1		-	-	-	
	Mental Well-being	9	24.29 [8.37; 44.57]	94.2		-	-	-	
	Others	4	20.02 [10.61; 31.36]	81.9		3	33.77 [17.01; 52.90]	94.9	
With CBT^b					0.41 1				0.65 4
	CBT ^b	17	21.35 [11.26; 33.41]	95.1		1 2	27.51 [20.16; 35.31]	94.5	
	No CBT ^b	9	11.64 [0.21; 33.29]	93.8		3	22.99 [7.94; 42.72]	92	
With Mindfulness					0.02 4 *				0.26 6
	Mindfulness	12	30.24 [17.02; 45.27]	95.5		1 1	23.89 [17.67; 30.71]	91.5	
	No Mindfulness	14	8.66 [0.89; 21.20]	92.8		4	34.35 [18.00; 52.84]	93.8	
Personalisation					0.63 3				0.52 9
	No personalisation	6	17.04 [5.08; 33.33]	84.7		2	38.10 [10.38; 70.94]	97.1	
	Minimal personalisation	2	44.57 [2.50; 92.50]	96.0					
	Substantial personalisation	9	21.56 [12.52; 32.12]	89.0		1 2	25.25 [19.16; 31.85]	91.3	
	Major personalisation	9	10.98 [0; 35.05]	96.5		1	19.51 [8.61; 33.23]	-	
CA^c Algorithm					0.42 3				0.48 6
	Rule-based	16	21.53 [11.72; 33.12]	93.1		1 3	25.02 [19.30; 31.19]	90.6	

	AI ^d -enhanced	10	13.25 [1.29; 32.79]	96.2		2	37.16 [8.05; 72.63]	95	
Type of CA^d					0.13 7				0.15 9
	No avatar	3	33.36 [15.39; 54.24]	94.3 6		1 2	29.21 [21.81; 37.19]	94. 6	
	ECA ^e	6	8.03 [1.37; 18.04]	59		2	15.35 [5.05; 29.63]	80. 3	
	Avatar	13	20.13 [6.67; 37.97]	96.4		1	19.51 [8.61; 33.23]	-	
	Not specified	4	15.15 [1.79; 35.93]	86.4					
Rewards					0.73 9				< .00 1 ^f
	With rewards	15	16.63 [9.93; 27.41]	92.4		1	54.83 [49.60; 60.00]	89. 9	
	No rewards	11	20.07 [5.77; 39.39]	96		1 4	24.68 [19.20; 30.59]		
Reminder					0.20 4				0.98
	With reminder	14	23.96 [12.19; 37.99]	94.8		7	26.42 [14.80; 39.96]	95. 7	
	without	12	11.43 [1.76; 26.27]	94.7		8	26.51 [17.85; 36.16]	92. 1	
Delivery Channel					0.02 f				< .00 1 ^b
	Web-based	4	30.74 [15.26; 48.70]	91.5		1 1	26.96 [20.73; 33.66]	90. 8	
	Computer/ Laptop / Tablet embedded program	6	4.72 [.06; 13.49]	61.5		1	9.33 [3.62; 17.12]	-	
	Smartphone app	10	14.32 [5.71; 25.56]	87.5		1	54.83 [49.60; 60.00]	-	

	Messenger-based	6	33.27 [10.58; 60.80]	96.9		1	19.51 [8.61; 33.23]	-	
	Not specified					1	22.11 [14.27; 31.06]	-	
Blended Design					0.37 6				0.01 8
	with Blended	3	19.12 [10.38; 29.56]	95.1		6	18.65 [12.86; 25.20]	75. 4	
	Without	23	9.89 [0.35; 26.31]	38.8		9	32.54 [23.01; 42.84]	94. 9	
Enrolment method					0.14 6				0.11 7
	Remote options only	14	26.63 [15.19; 39.82]	95.4		9	30.18 [20.38; 40.95]	95. 6	
	With in-person option	10	9.68 [15; 27.14]	92		6	21.28 [16.69; 26.26]	53. 7	
	Not specified	2	5.02 [0; 33.08]	88					
Study Population					0.05 ^f				0.40 8
	At-risk	11	19.92 [11.53; 29.81]	90.1		7	30.10 [17.09; 44.93]	96. 4	
	Clinical	4	3.53 [0; 13.05]	36		8	23.87 [18.55; 29.61]	76. 5	
	General	11	22.05 [6.73; 42.30]	96.1					
Session Length					0.61				0.33 9
	Defined session length	15	20.26 [9.93; 32.79]	94.1		1 4	27.05 [20.28; 34.38]	94. 3	
	User determined	11	15.31 [3.17; 33.12]	95.4		1	19.51 [8.61; 33.23]	-	
Symptom Trackers					0.99 8				0.00 3

	With Symptom Trackers	14	17.77 [6.44; 32.52]	93.9		6	16.36 [10.32; 23.39]	64. 1	
	Without Symptom Trackers	12	18.22 [7.21; 32.44]	95.3		9	33.48 [24.91; 42.62]	95. 4	

^aRCT = Randomized-controlled trial.

^bCBT = Cognitive-behavioral therapy.

^cCA = Conversational agent.

^dAI = Artificial intelligence.

^eECA = Embodied conversational agent.

^fSub-group analyses were not significant after dropping sub-groups with less than 5 studies.

For the overall attrition, there were significant differences in the attrition rates in short-term studies depending on the inclusion of mindfulness content, $\chi^2 (1) = 5.07, p = .02$. Interventions that included mindfulness content ($k = 12$) showed a higher rate of attrition in the intervention group, 30.24% (95% CI [17.02-42.27]), compared to interventions without mindfulness content, $k = 14$, 8.66 % (95% CI [0.89 – 21.20]). There were also significant differences depending on the population types, delivery channels, and types of disorders. However, these differences were not significant after excluding subgroups with less than 5 studies.

Subgroup analysis of the differential attrition rates showed that there were significantly different attrition rates in the intervention group relative to the control group participants depending on the sub-durations, $\chi^2 (1) = 5.77, p = .02$, between study populations, $\chi^2 (2) = 9.34, p = .009$ and types of control, $\chi^2 (1) = 4.68, p = .03$. The relative risks of attrition for studies that lasted between 5 to 8 weeks were significantly different, $k = 9$, log OR = 1.61 (95% CI [1.22, 2.13]), compared to studies that lasted less than 5 weeks, $k = 17$, log OR = 0.99 (95% CI [0.75, 1.31]). Studies that recruited at-risk populations ($k = 9$) showed significantly higher attrition rates in the intervention group compared to control group participants, 1.65 (95% CI [1.26; 2.15]), when compared to general populations, $k = 7$, log OR = 0.96 (95% CI [0.71; 1.30], and clinical populations, $k = 3$, log OR = 0.47 (95% CI [0.13; 1.66]). The subgroup analysis was still significant when compared between the general population and the at-risk group only, $\chi^2 (1) = 6.90, p = 0.03$. Lastly, studies that employed wait-list control, $k = 11$, log OR = 1.52 (95% CI [1.18, 1.95]), compared to active control, $k = 7$, log OR = 0.96 (95% CI [0.69; 1.54]). There were higher attrition rates in the intervention studies compared to wait-list controls relative to studies that used active control. There was only 1 study that used treatment-as-usual as the control group [90]. No other comparisons were significant.

Long-term studies (> 8 weeks)

The weighted attrition rate for the intervention group in long-term studies was 26.59% (95% CI [20.09, 33.63]) and there was evidence of high trial heterogeneity ($I^2 = 93.89\%$, (95% CI [91.43, 95.64])). The lowest relative attrition rate was 6.00% (95% CI[1.44, 16.84]) [55] and the highest was 54.83% (95% CI [49.61, 59.95]) [80].

Differential attrition differed from zero, log OR = 1.33 (95% CI [1.08, 1.65]) indicating that the attrition rates in the intervention group were higher than the control group. The heterogeneity was moderate ($I^2 = 49.43\%$ (95% CI [0.083, 72.11])). However, one study was identified as a potential outlier [54]. Removing this study from the model improved the I^2 greatly ($I^2 = 24.22\%$ (95% CI [0, 59.80])) and the differential attrition still differed from zero, log OR = 1.22 (95% CI [1.05; 1.42]) and this indicated again that the attrition rates in the intervention group were significantly larger than the control group even participants after removing the outlying study. The outlying study [54] used a

weighted randomization method in which 80% were allocated to the intervention group. The subgroup analyses were conducted without the outlier as the study appeared to explain more than 20% of the heterogeneity in the model. However, sensitivity analysis conducted with and without the outlying study did not change the results of the subgroup analysis.

Publication bias in long-term studies (> 8 weeks)

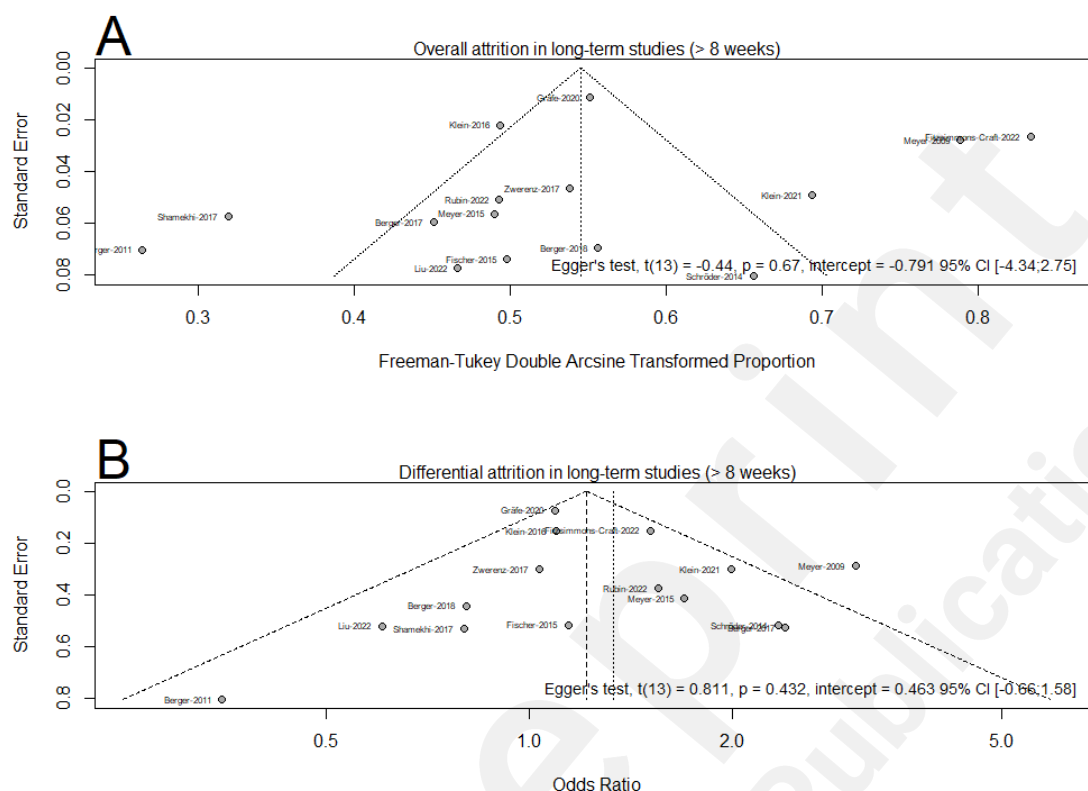


Figure 5. Funnel plots and Egger's test for publication bias for overall attrition (A) and differential attrition (B) in long-term studies.

For the overall attrition, the funnel plot indicated evidence of plot asymmetry, but Egger's test was not significant, intercept = -0.79 ; 95% CI $[-4.34, 2.75]$; $p = .67$, suggesting a low likelihood of publication bias. For the differential attrition, the funnel plot indicated evidence of plot symmetry and Egger's test was not significant, intercept = 0.46 ; 95% CI $[-0.66, 1.58]$; $p = .432$ (Figure 5).

Subgroup analyses of the attrition rates in long-term studies

For overall attrition, there were significant differences in the attrition rate in the intervention group of long-term studies that had a blended design, $\chi^2(1) = 4.68$, $p = 0.03$ and included symptom trackers or mood monitoring, $\chi^2(1) = 9.03$, $p = .003$. Interventions that included blended designs ($k = 6$) showed significantly lower attrition rates, 20.41% (95% CI $[15.49, 25.81]$) compared to those without, 33.30%, (95% CI $[23.01, 44.44]$), $k = 9$. Interventions that included symptom trackers ($k = 6$) showed significantly lower attrition rates, 16.36% (95% CI $[10.32; 23.39]$) compared to interventions without, 33.48% (95% CI $[24.91; 42.62]$, $k = 9$ (Table 3). No other comparisons were significant.

The differential attrition rates were significantly different across studies that included mindfulness content compared to those without, $\chi^2(1) = 5.00$, $p = .03$, and studies that targeted Depression symptoms compared to other mental health symptoms, $\chi^2(1) = 8.58$, $p = .003$. Studies without mindfulness intervention showed higher attrition rates in the interventions compared to controls, $k = 10$, log OR = 1.56 (95% CI $[1.25, 1.96]$, relative to studies that included mindfulness content, $k = 4$, log OR = 1.11 (95% CI $[1.05; 1.42]$). Studies that targeted Depression symptoms specifically showed

relatively similar attrition rates in both intervention and control groups, $k = 10$, $\log OR = 1.09$ (95% CI [0.96, 1.22]), relative to studies that targeted other mental health symptoms such as gambling disorder and substance abuse, $k = 4$, $\log OR = 1.63$ (95% CI [1.28, 2.08]). No other comparisons were significant.

Exploratory sub-group analyses

The overall weighted attrition rate for the intervention group in all included studies was 21.84% (95% CI [16.74, 27.36]), $I^2 = 94\%$. Exploratory sub-group analyses using the pre-specified subgroup analyses were conducted to explain the heterogeneity of the included studies regardless of the duration of the interventions. We included the full findings in Multimedia Appendix 5 and only highlight findings that differed from our prespecified analysis here. For the overall attrition, like our prespecified analysis, there were significant differences in the attrition rates in the intervention groups depending on the inclusion of mindfulness content, $\chi^2 (1) = 3.99$, $p = .05$. However, we did not find significant differences in the inclusion of blended support compared to non-blended intervention and symptom tracker. Additionally, we also found significant differences depending on the type of CA used, $\chi^2 (3) = 13.06$, $p = .005$; the CA delivery channel, $\chi^2 (4) = 21.27$, $p < .001$, and study enrolment method, $\chi^2 (2) = 7.44$, $p = .02$. Studies that did not use any identifiable avatar reported the highest rate of attrition, $k = 15$, 30.0% (95% CI [23.44; 37.01]), followed by studies that did not specify their use of avatar or visual representation of the CA, $k = 14$, 20.12% (95% CI [7.29; 36.82]), static avatar, $k = 4$, 15.15% (95% CI [1.79; 35.93]), and ECA, $k = 8$, 10.30% (95% CI [4.29; 18.04]). Interventions that were delivered via messenger-based intervention showed the highest rate of attrition, $k = 7$, 31.19% (95% CI [10.68; 56.28]), followed by web-based intervention, $k = 15$, 27.90% (95% CI [22.35; 33.78]), and standalone smartphone apps, $k = 11$, 17.36% (95% CI [6.54; 31.48]). CA installed on a computer, laptop, or tablet showed the lowest rate of attrition, $k = 7$, 5.61% (95% CI [1.09; 12.30]). Lastly, studies that offered remote onboarding only ($k = 23$) showed a higher attrition rate, 28.42% (95% CI [21.30; 36.10]) compared to studies that offered an in-person onboarding process, $k = 16$, 15.01% (95% CI [8.46; 22.82]).

The differential attrition differed from zero, $\log OR = 1.28$ (95% CI [1.10, 1.48]), $I^2 = 34.6\%$, indicating the participants who received CA-delivered interventions were more likely to attrit compared to the control group participants.

For differential attrition, our findings mostly concurred with our pre-specified analysis. Unlike the pre-specified analysis, there was a significant difference for studies that included symptom trackers, $\chi^2 (1) = 5.04$, $p = .02$. Studies that included symptoms tracker ($k = 17$) showed relatively lower attrition in the intervention group compared to the control group, $\log OR = 1.02$ (95% CI [0.81; 1.29]), compared to studies without symptoms tracker, $k = 18$, $\log OR = 1.44$ (95% CI [1.19; 1.74]).

Additional factors associated with attrition

16 (39%) studies assessed the association of different study features on participants' attrition of which 8 were short-term and 8 were long-term studies respectively. We grouped the findings into two categories, (1) demographic predictors and (2) baseline measurement predictors or symptoms severity.

The association between participants' demographics and attrition were assessed and reported in 10 studies. Of which, 4 were short-term and 6 were long-term studies. Only one short-term study found age to be significantly associated with attrition. Participants who dropped out were found to be significantly younger than those who completed the whole intervention [66]. Other demographics-related factors assessed in these 10 studies were not associated with attrition including gender, years of education, marital status, employment, actively receiving therapy, or medication, and current diagnosis for both short-term and long-term studies.

A total of 12 studies in total explored the association between baseline predictors or symptoms

severity and attrition of which 6 were short-term and 6 were long-term studies respectively. More severe baseline symptoms were associated with attrition for some short-term but not for long-term follow-up studies. Higher anxiety-related symptoms measured using General Anxiety Disorder-7 [66] and Visceral Sensitivity Index [27] were significantly related to attrition. Other factors found to be associated with higher attrition include lower quality of life measured using the World Health Organization Quality of Life Brief Questionnaire [56], higher Fear of Food score [27], higher severity of gambling pathology measured using the Pathological Gambling Adaptation of Yale-Brown Obsessive-Compulsive Scale [66], and lower self-esteem [84]. One study reported that participants with significantly greater positive affect measured using the Positive and Negative Affect Schedule were more likely to drop out compared to the completers [80].

Discussion

This systematic review and meta-analysis is the first, to our knowledge, to examine attrition in RCTs of CA-delivered interventions for mental health. Forty-one RCTs met the inclusion criteria. Our findings showed that around one-fifth of participants (18.05%) dropped out in short-term studies and about a quarter (26.59%) dropped out in long-term studies. Participants who received CA-delivered interventions were more likely to attrit compared to the control group participants for both, long and short-term studies. Several study-level moderators were identified. For short-term studies, higher overall attrition rates were found in intervention groups that included mindfulness content and those that included participants from the general population. Relative to the control group participants, participants in the short-term CA-delivered interventions were also more likely to attrit in studies that lasted more than 1 month; included at-risk participants; and were compared against wait-list controls as opposed to alternative active controls. For long-term studies, higher overall attrition rates were found in interventions that did not include human support and studies that did not include a symptoms tracker. Exploratory sub-group analyses conducted on all the included studies regardless of the study duration largely supported the analysis except for the inclusion of blended support. In addition, exploratory analyses found additional associations related to studies that used ECA, delivered via computer or smartphones, and provided in-person enrolment options were associated with lower attrition rates.

Comparison to prior research

Overall attrition

The overall attrition rates for short- and long-term studies in our review are lower than the attrition estimates of short- and long-term studies on smartphone-delivered interventions (24.1% and 35.5% respectively) [13] and e-mental health treatments for eating disorders (21%) [91]. Our findings are comparable to attrition in studies evaluating face-to-face mental health treatments such as interpersonal psychotherapy (20.6%) [92], individual psychotherapy for depressive disorders (19.9%) [93], and generalized anxiety disorders (17%) [94]. When focusing only on studies evaluating smartphone-delivered CAs in our review ($k=11$), we found that only 14.32% of participants dropped out of the short-term studies and 17.36% for all the included studies which were lower than the estimated attrition rate previously reported for smartphone-delivered mental health interventions [13]. Taken together, the delivery channel may indirectly influence study attrition [13]. While we found lower attrition in studies that were delivered via programs installed on a computer or laptop compared to other delivery channels, these studies [53,62,63,67,82] were conducted in a lab setting compared to the participants' environment which might influence the retention rate.

Factors associated with attrition

CA interventions used as adjuvants of psychotherapy sessions or with human support may aid in retaining participants, particularly in long-term studies. A closer look at the long-term studies that

included human support revealed that most of these studies used the CA-interventions as an adjunctive tool with no specific instruction given to the primary therapist on how to support participants' journey through the CA-interventions. This suggests that the presence of the therapist alone could suffice to retain participation in the study over a longer period. Although participants may be staying for the primary therapist and not engaging with the CA-intervention, a study with both therapist-guided and unguided groups found no significant differences in the time spent with the CA-intervention [55]. It is also possible that participants may have consulted their primary therapist about the CA-delivered interventions which were not reported by the studies. A recent scoping review reported that many studies that included human support did not consistently report the type of support provided by humans [95]. This was similarly observed in our study as none of the included studies mentioned whether the therapist discussed the CA-intervention within participants' routine sessions. Thirdly, it is also possible that participants within the clinical settings are more likely to stay with the intervention as was found in our results unrelated to the blended support provided. It is therefore difficult to conclude the impact of using CA-interventions adjunctively in terms of retaining participants within the study. This finding, however, should be taken with caution as we found that there were no significant differences in the attrition rate between studies that included blended and non-blended approaches when we included all the studies regardless of the study duration. This may be because fewer studies ($k = 9$ out of 41) included the blended approach overall. In terms of the intervention content, short-term studies that included mindfulness content had higher overall attrition rates compared to those without mindfulness content. This was contrary to two previous meta-analyses which showed that the inclusion of the mindfulness component had no impact on attrition rates [13,33]. The attrition rate however was similar to a systematic review of self-guided mindfulness intervention which reported an unweighted mean attrition rate of 31% (range: 0-79%) [96]. Future interventions may need to pay closer attention to participants' engagement when including mindfulness content as part of a CA-intervention. Factors such as utilizing symptom trackers and personalised feedback may increase the engagement rate [97]. This is aligned with our findings and prior meta-analyses that suggest including feedback may be impactful increase the retention rate [33].

Interestingly, our results also found relatively lower differential attrition in the intervention groups of long-term studies that included mindfulness compared to studies without. This finding, however, was not replicated when we analysed all the studies regardless of the study duration. A recent review suggested that longer mindfulness practices may be associated with the development mindfulness skills [96]. This result should therefore be interpreted cautiously as the relationship between the frequency and duration of mindfulness practices is still unclear [96].

Our study also found that including any form of CA visual representation may be associated with lower attrition rates compared to no visualization at all. This is aligned with many studies on the design of CA which stressed the importance of the CA design to create positive perceptions of the agent [98]. However, a recent scoping review reported that visual representation of the CA showed mixed and no association with subjective user experience [99]. A closer look at the studies included in this review suggested that most of the included studies lasted only 1 session [99]. It is possible that not having any CA visualization could affect user experience over time as alluded to by our findings. Future studies should explore the relationship between CA visual representation and user experience and study adherence over a longer duration.

In terms of the study sample population, at-risk sample populations were more likely to attrit compared to samples from general and clinical sample populations. However, other meta-analyses of digital intervention for mental health issues found no difference in attrition across sample populations [13, 33]. This finding is difficult to interpret as there could be multiple factors that may affect this relationship such as symptom severity and other demographic factors not included in the current analysis. Future studies may explore this relationship further to better understand this association.

Factors not associated with attrition

Providing monetary incentives did not affect the attrition rates significantly. This finding is similar to a previous meta-analysis focusing on smartphone apps specifically for depressive symptoms [33] but not smartphone interventions for mental health in general [13]. Time spent within the study may be a greater driver for attrition as can be seen in the higher attrition rates for longer studies found in our results. However, research on the impact of monetary incentives on participants' retention in digital health intervention is still in its infancy [100]. More needs to be done to understand how monetary incentives affect participants' retention as well as effective engagement in the intervention.

Lastly, several features such as providing reminders and the level of personalisation provided by the CA also did not affect attrition rates. This is noteworthy as a personalised intervention that is responsive to users' inputs is related to better engagement with the intervention [97]. There may be further nuances between attrition and effective engagement. For instance, factors that lower the risk of attrition might not be directly related to factors that promote study adherence [33].

Strengths and Limitations

We conducted a comprehensive literature search that included both peer-reviewed databases and grey literature sources as well as conducted backwards and forward citation searches. As this is a nascent area, we prioritized the sensitivity of our search to capture the various representations of CAs.

Our study, however, has some limitations. Firstly, some unpublished literature presented at niche conferences and meetings may have been omitted. Some studies might also escape our search strategy as evidenced by the inclusion of *deprexis* and *deprexis*-based interventions which did not explicitly mention “conversational agent” related terms in their studies. Secondly, the heterogeneity of the mental health conditions addressed by the CA-intervention made it difficult to generalize the findings to a specific disorder. The recommendations provided here should be taken as a general suggestion to improve retention rates in CA-delivered intervention for mental health but not for a specific mental health disorder. Thirdly, our results indicated possible publication bias in short-term studies. A closer look at the funnel plot suggested a lack of small sample-sized studies ($n < 20$) with high attrition rate in the intervention group. It is possible that these studies were not being published as they could be too experimental and small scaled. However, it is still possible that the findings are reported elsewhere in niche conferences and internal sharing which may have been omitted based on our search strategy. Fourthly, our results may not directly translate to understanding factors that may increase engagement with the interventions. While we recognise that engagement is interlinked with attrition [101], the lack of consensus and reporting of engagement metrics limits our understanding of this relationship. A recent review identified several patient-, intervention-, and system-level factors associated with engagement [102]. However, many of these associations were not consistent across different digital mental health interventions and there was poor consistency in the reporting of the metrics. We echoed others' recommendations to include and standardise the reporting of engagement metrics to better understand the indicators of non-usage attrition [97,101–103]. Our findings can inform future researchers of the potential factors for attrition in CA-delivered interventions. These may serve as a basis to make informed decisions on the sample size required or to conduct further studies on the specific mechanisms that may or may not motivate attrition. Lastly, our sub-group analyses for all the studies regardless of the intervention duration were exploratory post hoc analyses and should be interpreted as such.

Implications and recommendations

Several implications and recommendations emerged from our findings. First, researchers may want to account for about one-third of attrition when designing RCTs involving CA-delivered interventions. This number may need to be further adjusted depending on the sample population, delivery modes, and comparison group used in the intervention to minimize the potential threats to

the external and internal validity of studies that evaluate the efficacy of CA-delivered interventions for mental health. Second, researchers may want to consider including active controls in RCTs. Our results and findings from other similar reviews on attrition in digital health research [13,33] suggested that comparing digital interventions with waitlist controls might not be the ideal way as participants in the comparison group may be more motivated to remain in the study compared to those in the intervention group [13]. Control interventions consisting of periodic mood assessments via an app, or a non-conversational version of the app may be more appropriate for the assessment of CA effectiveness. Thirdly, the inclusion of a visual representation of the CA may help create a more positive perception of the CA and reduce attrition. A recent review suggested that design considerations such as having a human-like representation and having medical attire may be helpful to reduce attrition [99]. Fourthly, CA-interventions should be adjunctive to ongoing therapy sessions. While the association between attrition and the use of blended may be inconclusive, the use of CA-interventions may further enrich participants' experience between sessions and provide ongoing support to practice the skills learned during regular sessions. Lastly, clinicians interested in implementing CA-intervention in their practice should be aware of the high attrition rate and should closely monitor patient's progress within their practice.

Conclusions

According to our findings, at least one-third of the intervention group participants in RCT of CA-delivered mental health interventions will drop out of the trials within the intervention period. This is comparable to face-to-face mental health intervention and less than other digital health interventions. Furthermore, intervention group participants were more likely to drop out relative to the control group participants. Attrition was lower in studies with shorter duration studies, studies that included at-risk participants; and studies that were compared against wait-list controls as opposed to alternative active controls. Additionally, not including mindfulness content or symptom trackers was found to be associated with a smaller risk of attrition. Future studies may benefit from delivering CA intervention in a blended setting, with symptom screening, comparing the CA interventions against active controls such as symptom tracking only without the CA component, and including a visual representation of the CA to reduce attrition rates in the intervention group.

Declarations

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Conflict of interest

All authors declared that they have no competing interests.

Author contributions

LTC conceptualized the study and provided supervision at all steps of the research. LTC and AIJ designed the study. AIJ, XL, GS, and Nileshni Fernando extracted the data. AIJ conducted the analysis and wrote the original manuscript. LTC, LM, XL, GS, and YLT provided a critical review of the manuscript. All authors approved the final version of the manuscript and take accountabilities for all aspects of the work.

Availability of data and materials

This systematic review and meta-analysis do not contain primary data. The data will be made available by emailing the corresponding author.

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Abbreviations

AI: artificial intelligence.

CA: conversational agent.

CBT: cognitive-behavioral therapy.

ECA: embodied conversational agent.

OR: odds ratio

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

RCT: randomized-controlled trial.

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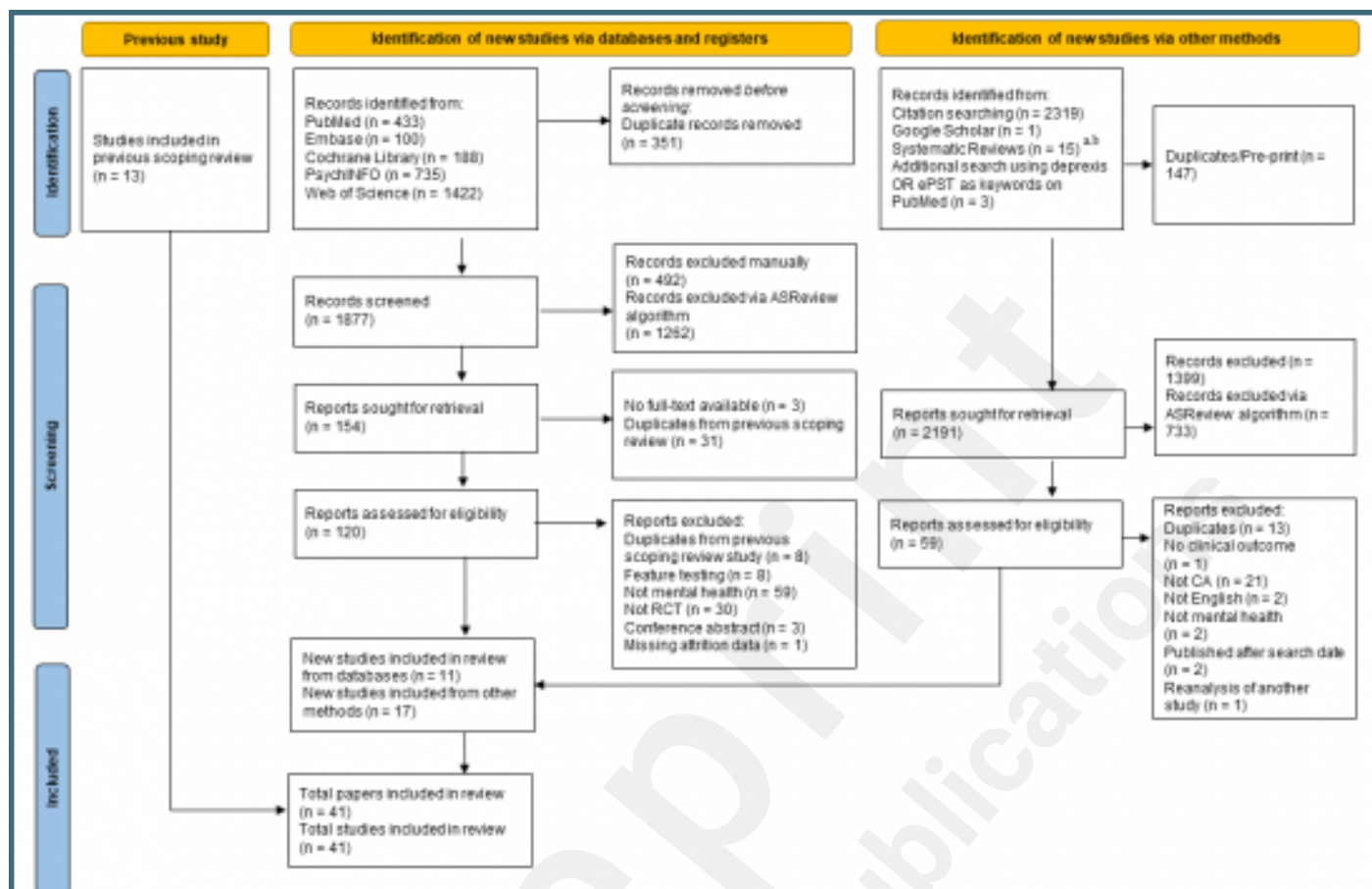
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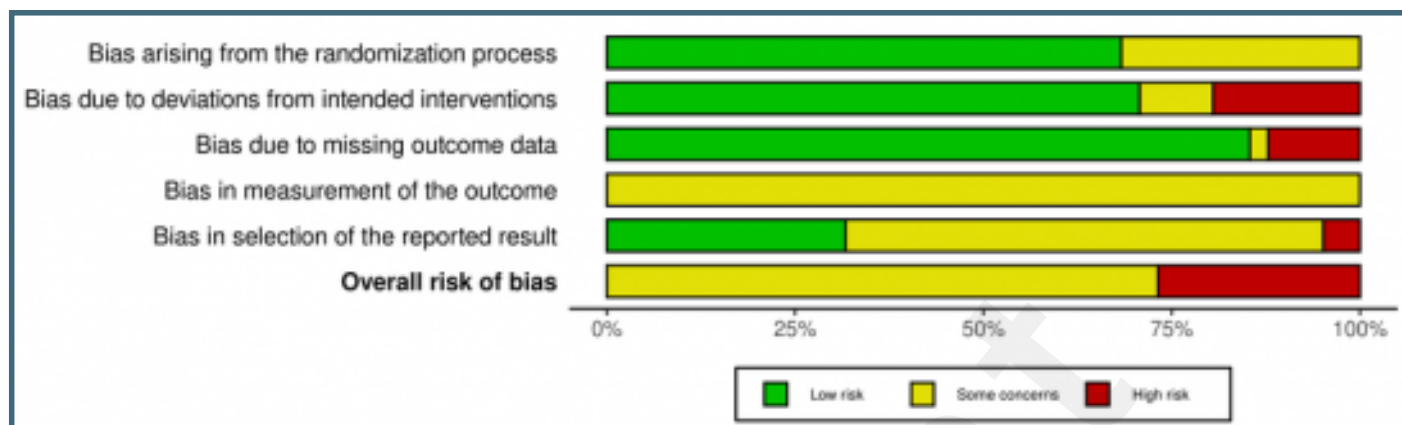
Supplementary Files

Figures

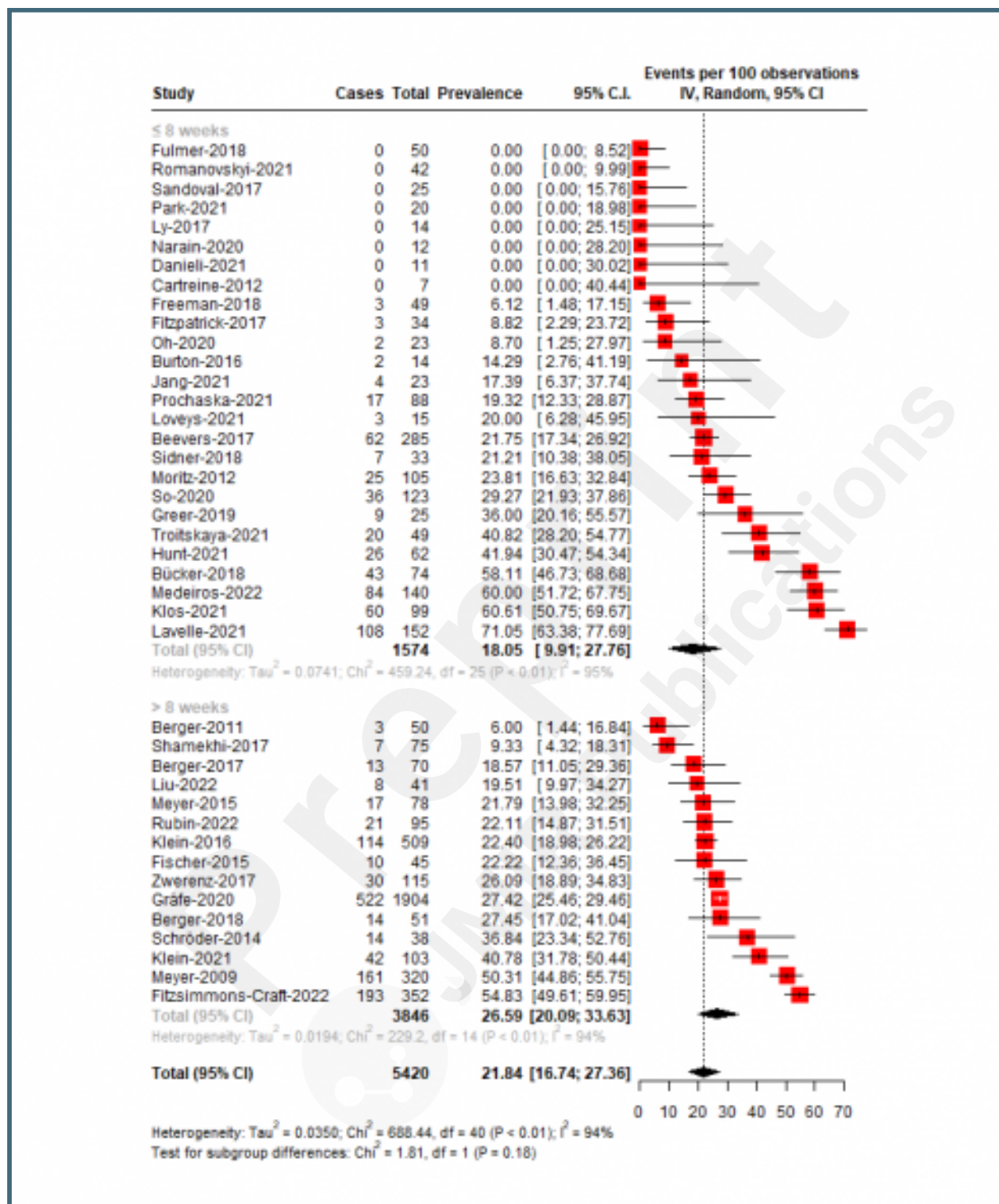
PRISMA Flowchart. a [19] b [51].



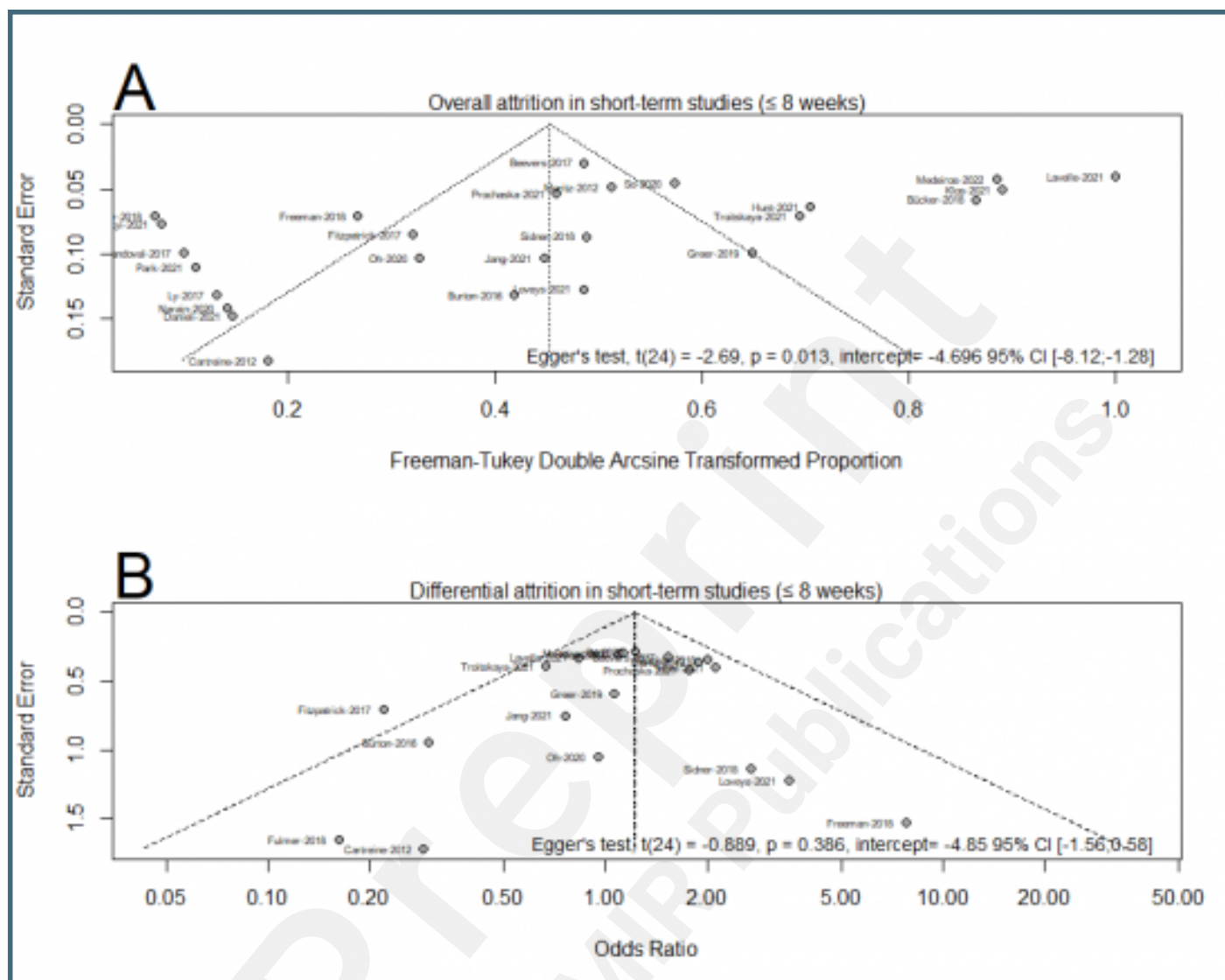
Summary plot for the risk of bias assessment for the included studies.



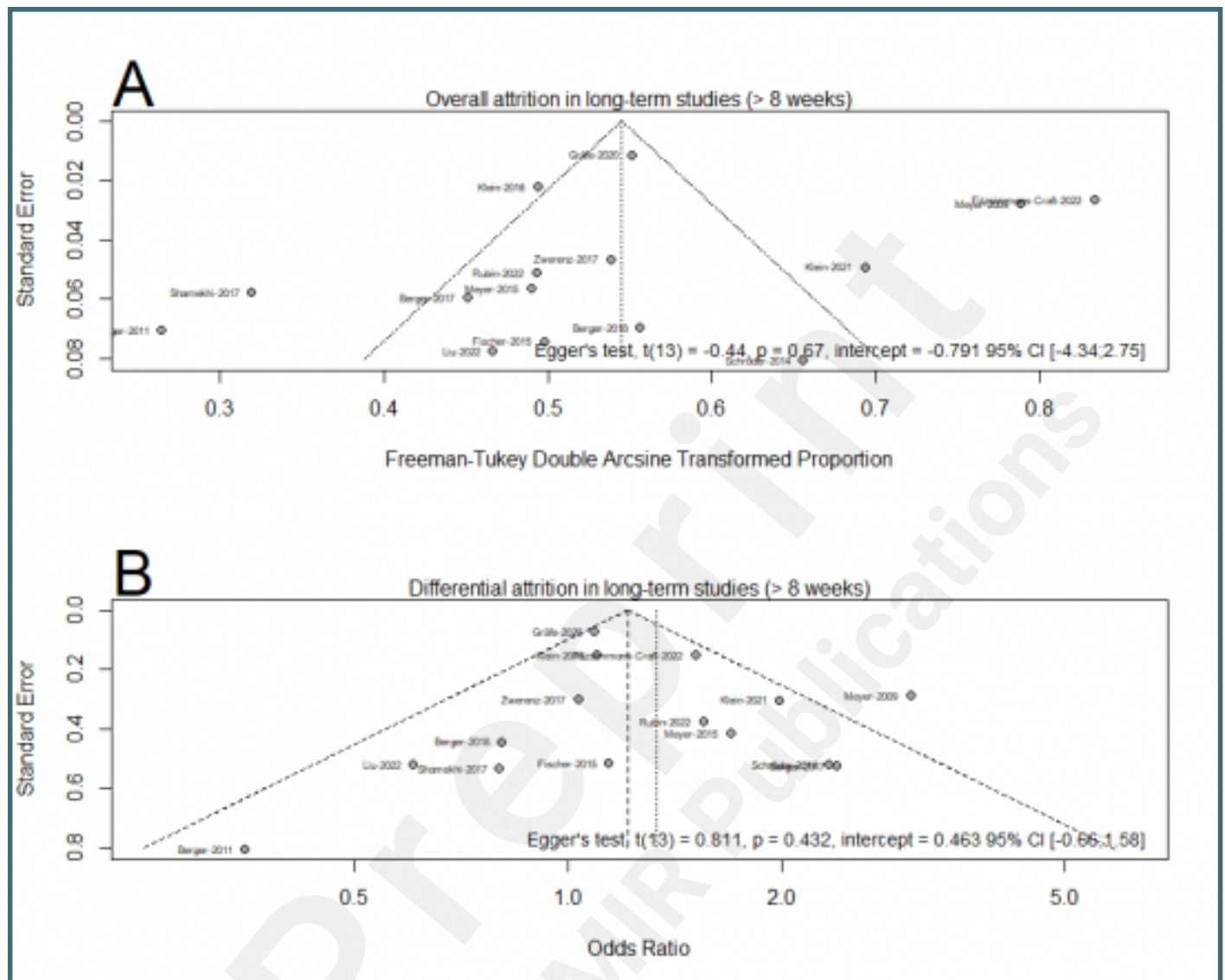
Overall attrition rates for the intervention group in CA-delivered mental health interventions.



Funnel plots and Egger's test for publication bias for overall attrition (A) and differential attrition (B) in meta-analyses of short-term studies.



Funnel plots and Egger's test for publication bias for overall attrition (A) and differential attrition (B) in long-term studies.



Multimedia Appendixes

Extended meta-analysis method.

URL: <http://asset.jmir.pub/assets/c081c4913bde519c294e9eb5dabc0ea6.docx>

Search strategy on PubMed.

URL: <http://asset.jmir.pub/assets/bdd42dcab6b0faab8a49d42e43262f23.docx>

Risk of bias assessment of the included studies.

URL: <http://asset.jmir.pub/assets/4e89516ea29ee1c8ed719275a928ad38.docx>

Differential attrition analysis for short- and long-term studies.

URL: <http://asset.jmir.pub/assets/f66bf3fa57b1bc7aa23b8889867d5bee.docx>

Extended result for the exploratory sub-group analysis.

URL: <http://asset.jmir.pub/assets/2ec87c33e4d35d90621a02c71bd4597c.docx>

Table of exclusion.

URL: <http://asset.jmir.pub/assets/7b68873f047343aba26731d44f2a24a6.docx>

CONSORT (or other) checklists

PRISMA Checklist.

URL: <http://asset.jmir.pub/assets/0e63a1b4d9778ae9ce275c3d886244b5.pdf>

TOC/Feature image for homepages

Attrition in conversational agent delivered mental health interventions: A systematic review and meta-analysis.

