### INTEGRATING DIGITAL APPROACHES FOR THE TREATMENT OF SUBSTANCE USE DISORDERS

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No relevant financial disclosures



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No relevant financial disclosures



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# Zoom Poll

#### GETTING TO KNOW THE AUDIENCE!

- Please indicate your primary degree.
- How do you spend most of your time in practice?
- How many years have you been treating patients with addiction?
- What is your primary work environment?
- What primary population do you and/or your team serve?



### Integrating Digital Approaches for the Treatment of Substance Use Disorders

This webinar provides an overview of the new digital approaches available that prescribing clinicians may find useful in the treatment of substance use disorder (SUD). It examines what the evidence says about their efficacy and explores strategies for integrating their use into practice as an adjunct to other evidence-based treatments in SUD treatment.

# Agenda

#### KEY TOPICS DISCUSSED IN THIS PRESENTATION

- Evolution of Digital Approaches and Key Terminology
- Summary of Digital Solutions for SUD Treatment
- Best Practices for Integrating Digital Approaches into SUD Treatment
- Q&A Sessions



Define basic terminology related to digital approaches in SUD.

Understand the landscape of digital approaches for SUD treatment.

# Learning Objectives

Evaluate digital tools that are evidence-based and differentiate the quality of various tools.

Identify patient characteristics that make use of digital approaches appropriate.

Examine best practices for implementing digital tools in your practices to supplement the current evidence-based treatments.



When poll is active, respond at PollEv.com/asamlearning370
 Text ASAMLEARNING370 to 22333 once to join

Please share a keyword or phrase that comes to mind when you think about digital interventions for substance use disorders.



Evolution of Digital Approaches

Presented by MARIO SAN BARTOLOME, MD, FASAM



### Evolution of Digital Approaches

#### Digital Health – an Umbrella

According to the US Food and Drug Administration (FDA), "digital health" includes categories such as mobile health, health information technology, wearable devices, telehealth/telemedicine, and personalized medicine.

Applications include support for clinical decision-making, leveraging artificial intelligence (AI), general wellness, monitoring, adjunctive use to other medical products.



Source: Food and Drug Administration https://www.fda.gov/medical-devices/digital-health-center-excellence/what-digital-health



#### Definitions Matter

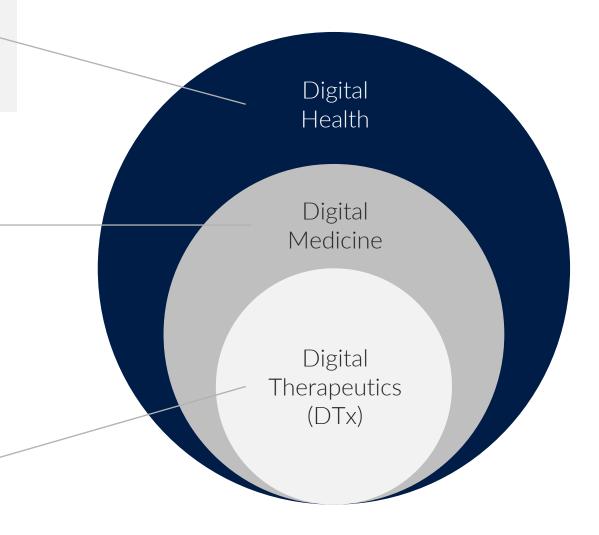


### **Digital Therapeutic (DTx):**

Digital therapeutics deliver medical interventions directly to patients using evidence-based, clinically evaluated software to treat, manage, and prevent a broad spectrum of diseases and disorders. They are used independently or in concert with medications, devices, or other therapies to optimize patient care and health outcomes.

- Entities that engage consumers for wellness and health-related purposes by obtaining health data.
- Do not require clinical evidence.
- Do not meet regulatory definition of a medical device and hence, do not require regulatory oversight.
- Evidence-based software and/or hardware products measuring human health.
- Require clinical evidence.
- Requirements for regulatory oversight vary.
- Products classified as medical devices require regulatory approval, while those used as a tool to develop other drugs, devices, or medical products require regulatory acceptance by the appropriate review division.

- Products delivering evidence-based therapeutic interventions to prevent, manage, or treat a disease.
- Require clinical evidence as well as data on real world outcomes.
- All DTx products must be reviewed and cleared or certified by regulatory bodies as required to support product claims of risk, efficacy, and intended use.







#### Digital Therapeutics in Behavioral Health

#### **Defined:**

Prescription digital therapeutics are software-based treatments delivered on mobile devices that address the behavioral dimensions of many diseases and conditions.

> Including Substance Use Disorders.

### Why are Digital Therapeutics Important?

**Access** to specialty SUD treatments with fidelity are limited

Eliminate **geographic** barriers to accessing treatment

Can be used as **adjuncts** to other, currently available treatments

Can be self-paced

Can be cost effective

Improves **engagement** often challenged by stigmatization

**Empowering** patients to be involved in their care

Allow for **personalization** 



### Digital Therapeutics in SUD Treatment



There is evidence that some digital therapeutics for SUD are safe, costeffective, and can improve treatment engagement.

#### Digital therapeutic tools allow for:

- Reduced Variability
- Standardization



### Patients & Clinicians

#### <u>Patient</u>

- Enrolled or engaged in SUD treatment
- Outpatient vs Inpatient
- Medications
- Open to Cognitive Behavioral Therapy
- Access to mobile device
- Access to internet/wireless connection for uploads

### <u>Clinician</u>

- Licensed Healthcare Clinician
- Access to a computer (dashboards)
- Provide SUD treatment with evidence-based modalities such as CBT or contingency management
- Digital Therapeutics are not intended to substitute face-to-face encounters







## Summary of Digital Solutions for SUD

Presented by Smita Das, MD, PhD, MPH



# Zoom Poll

Have you had experience with any of the following digital solutions for treating substance use disorders?

- Digital therapeutics
- Web Applications or Mobile Applications
- Guided Care with Apps
- Telehealth
- Social Media, Chatbots, Peer Support/Groups
- Wearables, Virtual Reality
- None of the above



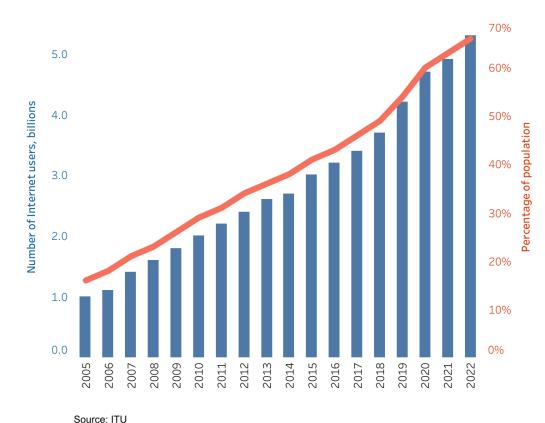
# Categories of Digital Solutions

- Digital therapeutics also referred to as DTx
- Applications or mobile applications not subject to regulatory review of digital therapeutics
  - Guided
  - Self-Guided
- Technology to deliver standard care like telemedicine
- Emerging areas
  - Social media
  - Chatbots
  - Peer support/groups
  - Wearables
  - Virtual reality



### Adoption of Internet and Mobile Technologies Has Skyrocketed

- 17% increase in internet usage since 2019
- 90% of population in developed countries uses internet
- 90% of population in ½ the countries owns a mobile phone









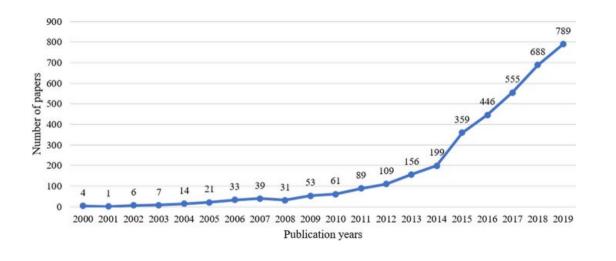
### Importance of Technology with SUD

- "5000-hour problem"
  - Patients only spend a few hours a year in front of a clinician
  - No data on 5000+ other waking hours of that year
- SUD is intertwined with daily activities and life, so potential to
  - Log use in real time
  - Use a relapse prevention plan at one's fingertips
  - Observe, discuss and influence choices in the moment
- Limited access and stigma with traditional treatment modalities

Asch DA, Muller RW, Volpp KG. Automated hovering in health care--watching over the 5000 hours. N Engl J Med. 2012 Jul 5;367(1):1–3.

## Scientific Approach to Review

Number of published papers related to e-mental health between 2000 and 2019, indexed by Clarivate Analytics tools



- The number of papers published in the area of e-mental health has grown rapidly in the last 5-10 years
- There is industry interest in publishing papers and quality/n can vary
- Throughout this part of the presentation, primarily reviews will be referenced



### Scientific Approach to Review (Cont.)

- Effect sizes
  - 0.20, 0.50, and 0.80 for Cohen's d (also known as SMD or standard mean difference) and Hedges' g are commonly considered
  - Small, medium, and large effects
- Targets of interest
  - Decrease in substance use
  - Retention in treatment
- Presentation will attempt to capture the current transitory state of the field



## Digital Therapeutics (DTx)



## Digital Therapeutics

- Mobile, web, or other software-based platforms or devices that deliver treatments for medical conditions or diseases (general wellness apps or telehealth)
- Can complement or even replace prescription drugs for managing certain health conditions
- Can make medical claims and must be device specific
- Must complete superiority trials (RCTs) to demonstrate at least equivalence of existing products or modalities or de novo value and safety



## Digital Therapeutics (Cont.)

- Subject to regulatory oversight since they get Food and Drug Administration (FDA) clearance
- Recent developments
  - Members of NIDA (National Institute of Drug Abuse) and the FDA support the development of safe and effective DTx for SUDs, noting they "offer unique treatment options and can deliver interventions with fidelity and state-of-the-art practices."
  - Legislation proposed to cover access to digital therapeutics in Medicare and Medicaid

Aklin WM, Walton KM, Antkowiak P. Digital therapeutics for Substance Use Disorders: Research priorities and clinical validation. Drug Alcohol Depend. 2021 Dec 1;229(Pt A):109120.

Lougheed T. How "digital therapeutics" differ from traditional health and wellness apps. CMAJ Can Med Assoc J. 2019 Oct 28;191(43):E1200–1.

Capito SM. S.3791 - 117th Congress (2021-2022): Access to Prescription Digital Therapeutics Act of 2022 [Internet]. 2022. Available from: http://www.congress.gov/



### Two SUD Prescription Digital Therapeutics

 Based on Therapeutic Education System (TES): Internet-delivered behavioral intervention that includes motivational incentives and serves as a clinicianextender in the treatment of substance use disorders

New York State Psychiatric Institute. NIDA-CTN-0044: Web-delivery of Evidence-Based, Psychosocial Treatment for Substance Use Disorders Using the Therapeutic Education System (TES) [Internet]. clinicaltrials.gov; 2017 Jul [cited 2022 Aug 7]. Report No.: NCT01104805. Available from: https://clinicaltrials.gov/ct2/show/NCT01104805 Campbell ANC, Miele GM, Nunes EV, McCrimmon S, Ghitza UE. Web-based, Psychosocial Treatment for Substance Use Disorders in Community Treatment Settings. Psychol Serv. 2012 May;9(2):212-4.

Commissioner O of the. FDA permits marketing of mobile medical application for substance use disorder [Internet]. FDA. FDA; 2020 [cited 2022 Aug 8]. Available from: https://www.fda.gov/news-events/press-announcements/fda-permits-marketing-mobile-medical-application-substance-use-disorder



### Two SUD Prescription Digital Therapeutics (Cont.)

- Reset: 90-day program, FDA cleared in 2017 to treat alcohol, cocaine, marijuana, and stimulant SUDs
  - CRA or Community Reinforcement Approach
  - Patient mobile app with a clinician interface delivering cognitive behavioral therapy through 61 modules (30 min of treatment each) + quizzes
  - Use with outpatient therapy and in addition to a contingency management (CM)
  - Study: Multisite, unblinded, 12-week clinical trial (n=399) of TAU or desktopbased version of reSET®
    - Statistically significant increase in adherence to abstinence for the patients with alcohol, cocaine, marijuana, and stimulant SUD in those who used reSET® (40.3%) compared with patients who did not (17.6%) (p=0.0004)
    - Not effective for opioid use disorder
    - Sponsor: New York State Psychiatric Institute | Collaborator: National Institute on Drug Abuse (NIDA)

k State Psychiatric Institute. NIDA-CTN-0044: Web-delivery of Evidence-Based, Psychosocial Treatment for Substance Use Disorders Using the Therapeutic Education System (TES) [Internet]. clinicaltrials.gov; 2017 Jul [cited 2022 Aug 7]. Report No.: NCT01104805. Available from: https://clinicaltrials.gov/ct2/show/NCT01104805



### Two SUD Prescription Digital Therapeutics (Cont.)

- reSET-O®, 84-day program, FDA cleared in 2018 to treat opioid use disorder (OUD)
  - Pair with buprenorphine treatment (17)
  - Study: Unblinded, controlled 12-week clinical trial (n=170) buprenorphine treatment paired with a behavior therapy program, either with or without the addition of a desktop-based version of reSET-O® for use in the clinic
    - reSET-O® did not decrease illicit drug use
    - Statistically significant increase in retention in a treatment program for 12 weeks for the patients who used the desktop computer version of the reSET-O® program (824%) compared to those who did not (68.4%) (p=0.02)
    - This study was sponsored by a grant from NIDA and the Wilbur Mills Endowment.
- Of note, the research settings had many resources that may not always be in place including CM, 30 min of face-to-face counseling every other week and 3x a week urine testing

Christensen DR, Landes RD, Jackson L, Marsch LA, Mancino MJ, Chopra MP, et al. Adding an Internet-delivered treatment to an efficacious treatment package for opioid dependence. J Consult Clin Psychol. 2014 Dec;82(6):964–72.

Commissioner O of the. FDA clears mobile medical app to help those with opioid use disorder stay in recovery programs [Internet]. FDA. FDA; 2020 [cited 2022 Aug 8]. Available from: https://www.fda.gov/news-events/press-announcements/fda-clears-mobile-medical-app-help-those-opioid-use-disorder-stay-recovery-programs

#### Clinical and Economic Review's Midwest Comparative Effectiveness Public Advisory Council Review

- Independent appraisal committees convened by Institute for Clinical and Economic Review for public deliberation of the evidence on clinical and cost-effectiveness
- Review of reSET-O® and two other commonly compared programs that do not have FDA clearance
  - Program 1: reSET-O®
  - Program 2: Digital CBT with a program that enhances patient communication with addiction experts, peer support groups, and counselors
  - Program 3: CBT + CM app with substance use screening results, Bluetoothenabled breathalyzer for alcohol testing, drug saliva testing, and appointment monitoring and reminders



# Clinical and Economic Review's Midwest Comparative Effectiveness Public Advisory Council Review (Cont.)

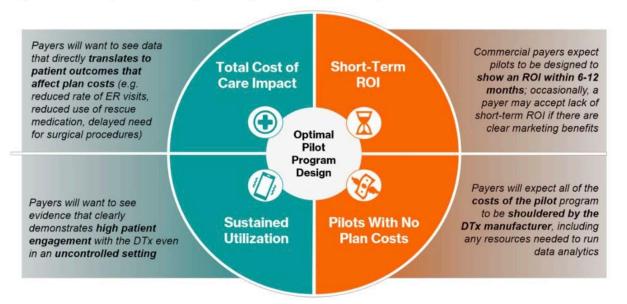
- Findings:
  - Council not confident in the effect on retention for reSET-O® and insufficient data for other two programs
  - Cost effectiveness analysis (only for reSET-O®): Cost per QALY ranged from approximately \$50,000 to \$500,000
  - Panel voted 10-3 that the clinical evidence was not adequate to demonstrate greater net health benefit for reSET-O® compared with best supportive care (13-0 for other two program)
- Take home: Due to the overwhelming value MAT (medications for addictions treatment) has, digital technologies must be carefully studied/implemented if used, to not negatively interfere with proven interventions; RCTs and better methodologies in development studies should be required



### Key Considerations

#### Image from Council Report:

Figure 3.1. Components of Optimal Digital Therapeutics Uptake<sup>43</sup>



- Costs high to develop
- Friction to get payment
- Hard to get adopters
- More research is needed for successful implementation and dissemination

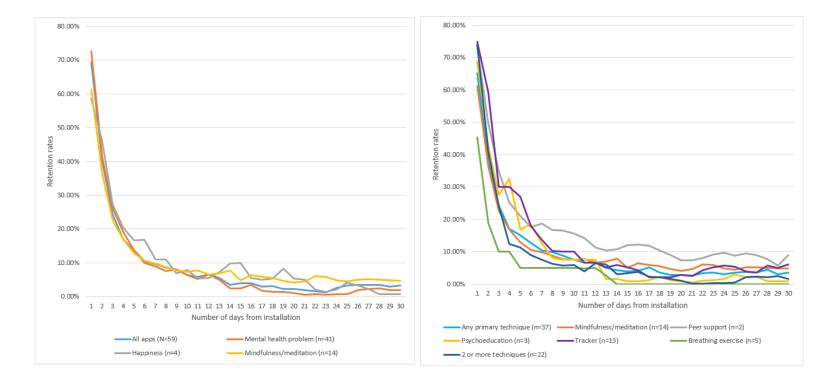


## Applications or Mobile Applications

(Generally, not subject to regulatory review of digital therapeutics.)



### >10K MH Apps (Software for a Mobile Device)



- Quality varies
- 2019 review: 93 apps with over 10,000 installs targeting anxiety, depression, or emotional well-being
- Median 4% daily active users, indicating possible low utility in practice and median 15–30-day retention in 3% range



# Lack of Reliable Research

- 2020 review: Only 2.08% (21/1009) apps for MH were supported by original research publications
  - 25 efficacy studies (8 from one vendor)
  - 10 feasibility studies
- Also included in this section are stand-alone websites, predecessors to mobile apps
- Can be guided or unguided





Lau N, O'Daffer A, Colt S, Yi-Frazier JP, Palermo TM, McCauley E, et al. Android and iPhone Mobile Apps for Psychosocial Wellness and Stress Management: Systematic Search in App Stores and Literature Review. JMIR MHealth UHealth. 2020 May 22;8(5):e17798.

# Existing Reviews

- 2019 review and meta-analysis of stand-alone apps for mental health concerns
  - 3 smoking cessation apps and 3 alcohol app studies there were small effects of the apps compared to control for smoking, no significant effects for alcohol and no significant difference when pooled
  - Guided interventions may increase efficacy
  - Adherence less impressive in standalone
  - Take home: how to design effective mental health apps is in infancy.

### Existing Reviews (Cont.)

- 2020 systematic review of apps for tobacco (n=6), alcohol (n=11), illicit drug use (n=1) or combinations (n=1
  - Research muddied by diverse comparison groups (like assessment only or paper-based interventions)
  - Only 6 of the 20 apps reported significant reductions in substance use at post or follow-up compared with a comparison condition, with small to moderate effect sizes
  - 3 of those were low quality studies (Image)
  - Take home: trials are not well powered and follow up times are insufficient
    - They also emphasize study pre-registration, adhering to guidelines and using theoretical models to guide design.

Weisel KK, Fuhrmann LM, Berking M, Baumeister H, Cuijpers P, Ebert DD. Standalone smartphone apps for mental health—a systematic review and meta-analysis. NPJ Digit Med. 2019 Dec 2;2:118. Staiger PK, O'Donnell R, Liknaitzky P, Bush R, Milward J. Mobile Apps to Reduce Tobacco, Alcohol, and Illicit Drug Use: Systematic Review of the First Decade. J Med Internet Res. 2020 Nov 24;22(11):e17156.

### Existing Reviews (Cont.)

	Random sequence generation	Allocation concealment	Blinding of participants and personnel	Blinding of outcome assessment	Incomplete outcome data
Aharonovich et al, 2017	•	œ	•	•	•
Baskerville et al, 2018	•	œ	۰	e	•
Boendermaker et al, 2015	•	٠	5	3	?
Bricker et al, 2014	?	?	۲	e	œ
Crane et al, 2018	•	œ	?	œ	•
Crane et al, 2018	•	•	?	•	•
Davies et al, 2017	•	•	Ð	•	÷
Earle et al, 2018	Ŧ	•	?	Ŧ	•
Gajecki et al, 2014	۲	۲	•	۲	•
Gajecki et al, 2017	۲	?	•	۲	?
Gonzalez & Dulin, 2015	•	٠	?	?	3
Gustafson et al, 2014	۲	•	۲	۲	•
Hasin et al, 2014	•	•	•	?	2
Hertzberg et al, 2013	?	?	?	?	•
Hides et al, 2018	Ŧ	?	?	Ð	œ
Kerst & Waters, 2014	?	?	•	•	•
Krishnan et al, 2018	?	?	?	•	•
Liang et al, 2018	?	?	?	?	•
Ruscio et al, 2016	۲	?	٠	•	•
Witkiewitz et al, 2014	?	?	?	•	?



## 2019 Meta-Analysis of CBT-Tech

- Gold standard approach to treat alcohol use disorder, often combined with motivational approaches, community reinforcement approach and mindfulness
- 2019 meta-analysis of CBT in computer or mobile form called "CBT tech" (15 studies)
- Controls were assessment, treatment as usual, psychoeducational reading and waitlist
- CBT tech compared to:
  - Minimal or no treatment found small positive effect at early follow up, but were non-significant at late follow up
  - Treatment as usual showed no significant differences



# 2019 Meta-Analysis of CBT-Tech (Cont.)

- CBT tech added to treatment as usual was helpful at both follow up times compared to just treatment as usual
- No difference was found between CBT tech versus therapist delivered, but notably the statistic (not significant) was negative for CBT Tech
- All effect sizes mentioned were small, with the largest (g=0.3) being for added CBT tech to treatment as usual



# 2019 Meta-Analysis of CBT-Tech (Cont.)

- Heterogeneous in design, content (4 vs 62 modules at 3 min each)
- Also incorporated MI/ME, not just CBT
- Adherence, engagement and exposure was also low for the majority of programs, as users could access at their will
- Reach on the other hand was huge for the interventions with the average RCT enrolling 656, with the largest being nearly 8,000 people and with diverse populations
- Take home:
  - While the effect sizes were small, the potential reach and potential effect of these interventions warrants more research.
  - These models should NOT replace in-person or established services, as there have been few well-controlled comparisons thus far



#### 2017 Cochrane Review of Digital Interventions for Alcohol Versus No Treatment or Face to Face

- Community settings like workplaces, colleges, clinics and internet users
- Aimed to assess the effectiveness and cost-effectiveness AND what behavior change components and theoretical bases were used
- 41 studies (42 comparisons, 19,241 participants)
- Findings:
  - Most people reported drinking less (23 grams of alcohol or 1.6 standard drinks) if they received advice about alcohol from a computer or mobile device compared to people who did not get this advice (studies were moderate quality) (Effect diminished over time)
  - Not enough data to differentiate the efficacy of computers, telephone or internet advice, but trusted virtual sources such as clinicians were more helpful as were specific recommendations
  - Only 5 studies compared digital advice (computers or mobile) to face to face conversations with doctors and nurses and there were little to no differences detected



# 2017 Cochrane Review of Digital Interventions for Alcohol Versus No Treatment or Face to Face (*Cont.*)

- Behavior change techniques:
  - Most common behavior change techniques were feedback on behavior (85.7%, n = 36), social comparison (81.0%, n = 34), information about social and environmental consequences (71.4%, n = 30) feedback on outcomes of behavior (69.0%, n = 29) and social support (64.3%, n = 27)
  - Interventions had an average 9 behavior change techniques with the most effective being (in an adjusted model): behavior substitution, problem solving and credible source
  - Behavior change techniques we use in traditionally use not in these studies (Self-monitoring, goal setting and review of behavioral/outcome goals have great efficacy)



# 2017 Cochrane Review of Digital Interventions for Alcohol Versus No Treatment or Face to Face (*Cont.*)

- Most common theories cited were Motivational Interviewing Theory (7/20), Transtheoretical Model (6/20) and Social Norms Theory (6/20)
  - Over half of the interventions (21) had no theory mentioned
- No intentionally used theory to guide recruitment
- Take home:
  - From a public health perspective, despite the small effect, with the low cost and wide reach of digital inventions, more research warranted
  - Digital interventions can be considered alongside face-to-face interventions as part of a strategy for addressing hazardous alcohol consumption and there is moderate quality evidence that digital interactions may reduce alcohol use compared to no treatment



#### Newer (2020) Review of Mobile Apps for Alcohol

- 19 unique apps in 21 studies (11 that were no longer available in app stores)
- 7 were for youth and 12 for adults.
- For young people, efficacy inconclusive with only 2/5 RCTs finding any significant reduction in alcohol consumption
- For adults, 7/12 had reductions in alcohol and 1 had a significant increase
- Take home from authors:
  - Hundreds of alcohol apps available and a few with peer review BUT evidence is underwhelming and in infancy
  - Still, potential in offering some intervention versus no intervention



# Guided Care with Apps



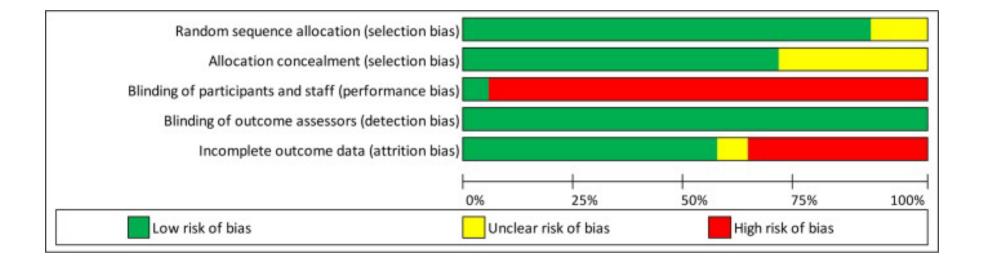
#### 2018 Review Investigated Internet-Based Alcohol Interventions (iAIs), Guided and Unguided

#### • Aims:

- Comment on whether usually underrepresented groups benefit (women and older people)
- Do varying levels of alcohol use benefit?
- Are guided or unguided are more effective?
- Individual patient data meta-analysis (IPDMA) with author collaboration
  - Identified 183 papers, 24 of which were eligible, 19 of which chose to participate.
  - 26 comparisons made, 19 of which were for unguided interventions
  - Outcome: standard units (SU) of alcohol use post intervention
    - Secondary outcome of treatment response (drinking 14 SUs [females] or 21 SUs [males]) at varying times of follow up
- Of the 14,198 enrolled participants, 8,095 provided post-intervention data (mean weekly SU baseline=38.1)
- Studies were considered relatively high quality based on Cochrane Collaboration risk-of-bias assessment tool



#### 2018 Review Investigated Internet-Based Alcohol Interventions (iAls), Guided and Unguided (*Cont.*)





Riper H, Hoogendoorn A, Cuijpers P, Karyotaki E, Boumparis N, Mira A, et al. Effectiveness and treatment moderators of internet interventions for adult problem drinking: An individual patient data meta-analysis of 19 randomised controlled trials. PLoS Med. 2018 Dec 18;15(12):e1002714.

#### 2018 Review Investigated Internet-Based Alcohol Interventions (iAIs), Guided and Unguided (*Cont.*)

- Controls were largely psychoeducational material, assessment only and waitlist controls (WLC)
- Outcomes
  - Compared to controls, iAI participants had a significant difference in mean weekly alcohol reduction (5 SUs) and treatment response
  - Women had a less robust reduction in drinks than men
  - >55-year-old participants had a better treatment response than those who are younger
  - Guided interventions and therapeutic principal interventions (versus just personalized normative feedback) were also more helpful
  - WLC studies had a greater effect size (may be participants delaying changes in alcohol use)



#### 2018 Review Investigated Internet-Based Alcohol Interventions (iAls), Guided and Unguided (*Cont.*)

Forest plot of conventional meta-analysis iAi's versus controls

Study name	Outcome		S	tatistics	for eac	h study	/			Hedges's g and 95% Cl				
		Hedges's g	Standard error	Variance	Lower limit	Upper limit	Z-Value	p-Value	-	1		T		
Araki 2006	drinks/day	0.336	0.232	0.054	-0.119	0.791	1.448	0.148					- 1	
Bertholet 2015	drinks/week	0.044	0.074	0.005	-0.101	0.188	0.592	0.554						
Bischof 2007a	combined	0.126	0.148	0.022	-0.163	0.415	0.853	0.394		-		_	I	
Bischof 2007b	combined	0.097	0.146	0.021	-0.190	0.383	0.660	0.509		-				
Blankers 2011a	drinks/lastweek	0.588	0.211	0.044	0.176	1.001	2.795	0.005		100	_			
Blankers 2011b	drinks/lastweek	0.346	0.210	0.044	-0.066	0.757	1.647	0.100			+			
Boon 2006	drinks/week	0.261	0.145	0.021	-0.023	0.545	1.800	0.072						
Boon 2011	drinks/week	0.281	0.109	0.012	0.067	0.495	2.578	0.010						
Boss 2017a	drinks/week	0.249	0.144	0.021	-0.033	0.531	1.728	0.084					I	
Boss 2017b	drinks/week	0.350	0.145	0.021	0.066	0.634	2,419	0.016						
Brendryen 2013	drinks/week	0.136	0.128	0.016	-0.114	0.387	1.066	0.286				_		
Brendryen 2017	drinks/week	0.236	0.216	0.047	-0.187	0.659	1.094	0.274		-				
Cunningham 2009	drinks/week	0.277	0.234	0.055	-0.182	0.737	1.182	0.237		-	_			
Delrahim 2011a	combined	0.200	0.172	0.029	-0.136	0.537	1.167	0.243						
Doumas 2008a	drinks/weekend	0.312	0.457	0.209	-0.584	1.208	0.683	0.495					$\rightarrow$	
Doumas 2008b	drinks/week	0.092	0.487	0.238	-0.863	1.048	0.189	0.850					$\rightarrow$	
Fingfeld 2008	drinks/day	0.552	0.370	0.137	-0.174	1.277	1.491	0.136		-			$\rightarrow$	
Hansen 2012a	drinks/week	0.040	0.081	0.007	-0.119	0.200	0.496	0.620						
Hansen 2012b	drinks/week	0.137	0.081	0.007	-0.021	0.295	1.696	0.090						
Hester 2005	drinks/day	0.511	0.260	0.067	0.002	1.020	1.966	0.049				_	$\rightarrow$	
Khadjesari 2014	drinks/week	-0.044	0.055	0.003	-0.152	0.063	-0.804	0.421				T		
Pemberton 2011a	combined	0.279	0.144	0.021	-0.005	0.562	1.929	0.054						
Pemberton 2011b	combined	0.148	0.155	0.024	-0.156	0.452	0.956	0.339			_	_		
Postel 2010	drinks/week	1.204	0.173	0.030	0.864	1.543	6.945	0.000			1000		$\rightarrow$	
Riper 2008	drinks/week	0.522	0.126	0.016	0.275	0.769	4.143	0.000					.	
Schultz 2013b	drinks/week	0.337	0.163	0.027	0.018	0.657	2.070	0.038					I	
Schulz 2013a	drinks/week	0.260	0.168	0.028	-0.069	0.589	1.548	0.122					I	
Sinadovic 2014a	drinks/week	-0.100	2.005	4.021	-4.030	3.831	-0.050	0.960	<del>~ ~</del>			_		
Sinadovic 2014b	drinks/week	0.100	2.005	4.021	-3.831	4.030	0.050	0.960	<del>&lt; -</del>			_		
Suffoletto 2012a	drinks/drinkday	0.395	0.449	0.201	-0.484	1.274	0.881	0.378			_		$\rightarrow$	
Suffoletto 2012b	drinks/drinkday	-0.654	0.488	0.239	-1.611	0.304	-1.338	0.181	<del>&lt;</del>		_			
Sundstrom 2016a	drinks/week	0.663	0.319	0.102	0.038	1.288	2.080	0.038		1000			$\rightarrow$	
Sundstrom 2016b	drinks/week	0.840	0.324	0.105	0.205	1.474	2.593	0.010			_		$\rightarrow$	
Wallace 2011	drinks/week	0.036	0.056	0.003	-0.074	0.146	0.641	0.521			-			
		0.257	0.045	0.002	0.1690	0.345	5.711	0.000			-			
									-1.00	-0.50	0.00	0.50	1.0	
										Favours Contro	I Favou	urs Experiment	al	

- Meta-analysis: Small significant difference in mean weekly SUs at the first follow-up in favor of iAl participants (Hedges' g = 0.26, 95% CI 0.17–0.34, p < 0.001).</li>
- Take home:
  - IPDMA method provided greater power and some insights into how iAI can be a helpful first step for many people.
  - Not all treatment participants benefited from iAls, so more research is needed to understand which people such interventions work for and in what contexts



Riper H, Hoogendoorn A, Cuijpers P, Karyotaki E, Boumparis N, Mira A, et al. Effectiveness and treatment moderators of internet interventions for adult problem drinking: An individual patient data meta-analysis of 19 randomised controlled trials. PLoS Med. 2018 Dec 18;15(12):e1002714.

#### 2018 Review and Meta-analysis of 30 Studies for Cannabis

- Studies:
  - 10 prevention- 4 guided/6 unguided (comparison either prevention as usual or assessment only)
  - 20 treatment- 8 guided/12 unguided (comparison largely education and assessment only)
  - 21 for the meta-analysis (6 prevention and 15 treatment)
- Quality of studies was low based on the Cochrane risk-of-bias tool
- Outcomes:
  - Prevention programs: Associated with reduction in cannabis use at post treatment and follow up (Image 1)
  - Treatment programs were mildly significant at post treatment but not at follow up (Image 2)



# 2018 Review and Meta-Analysis of 30 Studies for Cannabis (Cont.)

Assessment Herdges      Standari B      Correct Form      Correct F	Study name	me Statistics for each study								Hedges's g and 95% CI						
Hind, 2012    Post-treatment    0.43    0.13    0.017    0.09    0.64    2.65    0.037      Schinkz, 2000    Post-treatment    0.43    0.035    0.035    0.037    2.135    0.037      Schinkz, 2000    Post-treatment    0.140    0.017    0.048    0.560    2.329    0.020      Schinkz, 2000    Post-treatment    0.130    0.017    0.048    0.560    2.329    0.020      Schinkz, 2000    Post-treatment    0.140    0.055    0.021    0.31    2.016    0.016      Schinkz, 2000    Post-treatment    0.180    0.066    0.001    0.227    0.301    2.118    0.007      Schinkz, 2000    Polowup    0.300    0.116    0.32    2.016    0.016    0.022    0.007    0.016    0.028    0.016    0.006    0.000		Assessment He	0													
Frag. 2010    Post-treatment    0.421    0.197    0.033    0.035    0.007    2.135    0.003      Schinkz, 2000b    Post-treatment    0.643    0.068    0.007    0.017    9.495    0.003      Schinkz, 2000b    Post-treatment    0.340    0.131    0.017    0.448    0.500    2.329    0.020      Walton, 2014    Post-treatment    0.320    0.010    0.005    0.331    0.017    0.048    0.560    2.329    0.020      Schinkz, 2000b    Follow-up    0.305    0.017    0.048    0.562    2.329    0.020      Schinkz, 2000b    Follow-up    0.305    0.017    0.048    0.562    2.329    0.020      Walton, 2014    Follow-up    0.305    0.013    0.017    0.048    0.522    2.329    0.020      Statistic Sore care in study    Extenses    Extenses    Core    Up    Up <thup< th="">    Up    Up<td></td><td></td><td>g</td><td>error</td><td>Varia</td><td>nce lin</td><td>nit lir</td><td>nit Z-</td><td>Value p-V</td><td>/alue</td><td></td><td></td><td></td><td></td></thup<>			g	error	Varia	nce lin	nit lir	nit Z-	Value p-V	/alue						
Schinke, 2009a    Post-treatment    0.643    0.006    0.007    0.976    9.495    0.000      Schinke, 2009b    Post-treatment    0.164    0.083    0.007    0.0048    0.501    0.277    9.495    0.000      Walton, 2014    Post-treatment    0.300    0.131    0.017    0.048    0.502    0.239    0.100    0.150      PooLED    0.322    0.105    0.011    0.107    0.048    0.507    1.314    0.001      Schinke, 2009b    Follow-up    0.655    0.198    0.039    0.268    1.042    3.314    0.001      Schwim, 2010    Follow-up    0.265    0.007    0.006    0.007    0.312    2.433    0.010      Schwim, 2010    Follow-up    0.325    0.033    0.16    0.332    4.071    0.000      Staty name    Edges's gand 93% CE    Edges's gand 95% CE    Edges's gand 95% CE    Edges's gand 95% CE      Becker, 2014    Post-treatment    0.000    0.164    0.277<-0.327	,		0.349	0.130	0.017	0.094	1 0.604	1 2.6	82 0.00	)7			──₩┼─			
Schimkz 2009b    Pest-treatment    0.168    0.007    0.007    0.001    0.031    2.016    0.044      Schwim, 2010    Pest-treatment    0.131    0.017    0.048    0.502    2.329    0.020      Fang, 2010    Follow-up    0.655    0.198    0.039    0.268    1.042    3.314    0.001      Schimkz, 2009b    Follow-up    0.180    0.066    0.007    0.041    0.311    0.017      Schimkz, 2009b    Follow-up    0.180    0.066    0.007    0.281    1.861    0.007      Schwinz, 2010    Follow-up    0.140    0.075    0.006    0.007    0.287    1.861    0.063      Schwinz, 2010    Follow-up    0.140    0.075    0.007    0.287    1.861    0.063      Walton, 2014    POOLED    0.237    0.003    0.297    1.861    0.063    0.064    0.065    0.075      Walton, 2014    Post-treatment    0.000    0.167    0.028    0.327    0.207    0.000    0.000      Schwinz, 2012    Post-treatment    0.000    0.174	0,		0.421	0.197	0.039	0.035	0.80	7 2.1	35 0.03	33				_		
	Schinke, 2009a	Post-treatment	0.643	0.068	0.005	0.510	0.776	5 9.4	95 0.00	00			H	-		
Walton, 2014    Pest-treatment    0.120    0.001    0.008    0.006    0.029    1.310    0.190      Fang, 2010    Follow-up    0.655    0.019    0.028    0.024    3.314    0.001      Schinke, 20004    Follow-up    0.180    0.066    0.004    0.050    0.310    2.718    0.001      Schwike, 20004    Follow-up    0.305    0.011    0.017    0.044    0.322    2.329    0.002      Walton, 2014    Follow-up    0.305    0.005    0.003    0.116    0.322    4.071    0.003      Schwin, 2014    Follow-up    0.224    0.025    0.003    0.116    0.322    4.071    0.004      Schwin, 2014    Post-treatment    0.000    0.164    0.027    0.321    0.201    0.000    1.000      Instoff, 2014    Post-treatment    0.000    0.164    0.027    0.321    0.201    0.204    0.775      Becker, 2014b    Post-treatment    0.010    0.164    0.027    0.321    0.217    0.226    0.775      Becker, 2014    Post-treatme	Schinke, 2009b	Post-treatment	0.168	0.083	0.007	0.005	5 0.33	2.0	16 0.04	14						
POOLED    0.132    0.013    0.010    0.127    0.337    3.175    0.001      Schinke, 20096    Follow-up    0.655    0.198    0.039    0.268    1.042    3.314    0.001      Schinke, 20096    Follow-up    0.266    0.084    0.007    0.041    0.371    2.453    0.014      Schwin, 2010    Follow-up    0.305    0.131    0.017    0.048    0.522    2.329    0.020      Walton, 2014    Follow-up    0.305    0.035    0.030    0.116    0.332    4.071    0.000      Study name    Statistics for each situs    Edges's and 95% CI    Edges's and 95% CI    Edges's and 95% CI      Becker, 2014    Post-treatment 0.000    0.164    0.027 - 0.321    0.321    0.000    1.000      Christoff, 2015    Post-treatment 0.000    0.164    0.027 - 0.321    0.321    0.000    1.000      Christoff, 2015    Post-treatment 0.030    0.211    0.013 - 0.180    0.221    0.286    0.775      Ellid, 2016    Post-treatment 0.031    0.221    0.046    0.231    0.230    0.8980 </td <td>Schwinn, 2010</td> <td>Post-treatment</td> <td>0.304</td> <td>0.131</td> <td>0.017</td> <td>0.048</td> <td>0.560</td> <td>2.3</td> <td>29 0.02</td> <td>20</td> <td></td> <td></td> <td></td> <td></td>	Schwinn, 2010	Post-treatment	0.304	0.131	0.017	0.048	0.560	2.3	29 0.02	20						
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Walton, 2014	Post-treatment	0.120	0.091	0.008	-0.060	0.299	1.3	10 0.19	90						
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $		POOLED	0.332	0.105	0.011	0.127	0.53	7 3.1	75 0.00	01						
Schinke, 2009b    Follow-up    0.180    0.066    0.004    0.050    0.310    2.718    0.007      Schinke, 2009b    Follow-up    0.206    0.084    0.007    0.041    0.371    2.435    0.017      Schwinz, 2014    Follow-up    0.140    0.075    0.006    -0.027    0.287    1.861    0.063      Study name    Edges's    Standar    Edges's    Standar    Edges's    1.861    0.063      Becker, 2014b    Post-treatment 0.000    0.167    0.022    0.321    0.000    1.000      Becker, 2014b    Post-treatment 0.000    0.167    0.022    0.232    0.231    0.000    1.000      Christoff, 2015    Post-treatment 0.003    0.174    0.033    0.400    1.039    0.890      Christoff, 2015    Post-treatment 0.031    0.221    0.049    -0.030    0.450    0.890      Christoff, 2014    Post-treatment 0.031    0.221    0.049    0.032    0.120    0.286    0.776      Gryczynski, 2016    Post-treatment 0.031    0.221    0.040    0.032    0.286    0.77	Eana 2010	Follow-up		0 198				> 33	14 0.00	01			_			
Schnike, 2009 Schwir, 2010      Follow-up Follow-up POOLED      0.206 0.305      0.084 0.007      0.041 0.48      0.52 0.232      0.014 0.003      0.014 0.005      0.031 0.006      0.014 0.005      0.032 0.028      0.014 0.000      0.014 0.000      0.014 0.000      0.028      0.232 0.028      0.014 0.000      0.014 0.000      0.016      0.032 0.005      0.003 0.016      0.032 0.000      0.006      0.007 0.000      0.000 0.000      0.000	0.	-												- 1		
Schwinn, 2010      Follow-up Follow-up      0.305      0.131      0.017      0.048      0.562      2.329      0.020        Sthwinn, 2014      Follow-up      0.140      0.075      0.006      -0.07      0.287      1.861      0.063        Sthwinn, 2014      Follow-up      0.140      0.075      0.003      0.116      0.332      4.071      0.000        Study name      Etedges's      Standard      Ever Uper      Follow-up      0.164      0.027      0.321      0.000      1.000        Becker, 2014b      Post-treatment 0.000      0.167      0.028      0.327      0.327      0.321      0.000      1.000        Chrome total      Post-treatment 0.000      0.167      0.028      0.327      0.286      0.775        Elido, 2014      Post-treatment 0.031      0.221      0.049      0.035      0.240      0.035      0.896        Chrome streatment 0.031      0.221      0.049      0.035      1.240      2.074      0.038      0.896        Chrome streatment 0.046      0.176      0.022      0.023      0.982      0	,															
Schwinn, 2010    Follow-up    0.033    0.013    0.004    0.007    0.0287    1.861    0.063      Walton, 2014    POOLED    0.224    0.055    0.003    0.116    0.332    4.071    0.000      Study name    Editistics for each study    Edges's g and 95% CI      Edges's    Statistics for each study    Edges's g and 95% CI      Becker, 2014a    Post-treatment 0.000    0.164    0.027    0.321    0.321    0.000    1.000      Christoff, 2015    Post-treatment 0.000    0.164    0.028    0.232    0.284    0.776    0.038    0.890      Gryczynski, 2016    Post-treatment 0.031    0.221    0.049    0.403    0.465    0.139    0.890      Jonas, 2012    Post-treatment 0.031    0.221    0.049    0.032    0.028    0.377    0.038    0.397    0.044    0.390    0.231    0.231    0.321    0.001    0.001    0.016    0.023    0.482    0.774    0.782    0.774    0.782    0.774      Gryczynski, 2016    Post-treatment 0.046    0.177    0.023	,	-														
Waldur, 2017      POOLED      0.224      0.055      0.003      0.116      0.332      4.071      0.000        Study name      Statistics for each study      Hedges's g and 95% CI        Mascsment      g error      Variance limit limit      Cover Variance limit limit      Hedges's Cover Variance limit limit Z-Value-Value        Becker, 2014      Post-treatment 0.000      0.164      0.027      0.321      0.201      0.000      1.000        Becker, 2014      Post-treatment 0.033      0.112      0.031      0.320      0.221      0.286      0.775        Ellid, 2014      Post-treatment 0.036      0.211      0.028      0.221      0.286      0.775        Ellid, 2014      Post-treatment 0.036      0.221      0.048      0.423      0.174      0.035      1.240      2.074      0.288        Gryczynski, 2016      Post-treatment 0.036      0.243      0.030      0.243      0.030      0.258      0.774        Codesma, 2007      Post-treatment 0.046      0.176      0.032      0.403      0.243      0.030      0.258      0.774        Rooke, 2013      Post-treatme	,															
Status      Status      Decks      Status        Particit      Index      <	Walton, 2014	-														
Hedges's      Standard      Lower      Upper        Assessment      g      error      Variance limit      limit      Z-Value        Becker, 2014      Post-treatment 0.000      0.164      0.027      -0.321      0.321      0.000      1.000        Christoff, 2015      Post-treatment 0.003      0.174      0.030      -0.390      0.291      -0.286      0.775        Ellid, 2016      Post-treatment 0.031      0.221      0.049      -0.403      0.455      0.139      0.880        Jonas, 2012      Post-treatment 0.031      0.221      0.049      -0.035      1.240      0.035      1.240      0.035        Condersma, 2017      Post-treatment 0.026      0.164      0.039      -0.238      0.982      0.038      0.037        Ondersma, 2014      Post-treatment 0.262      0.179      0.032      -0.438      0.037      0.037      0.031      -0.233      0.446      0.541      1.475      0.140      0.539        Condersma, 2014      Post-treatment 0.166      0.173      0.030      -0.233      0.446      0.541      0.574      0.		POOLED	0.224	0.055	0.003	0.116	0.332	2 4.0	71 0.00	00	I	1				
Assessment      g      error      Variance      limit      limit      Z-Valuep-Value        Becker, 2014a      Post-treatment      0.000      0.164      0.027      0.321      0.000      1.000        Becker, 2014b      Post-treatment      0.000      0.167      0.028      0.327      0.327      0.000      1.000        Christoff, 2015      Post-treatment      0.032      0.112      0.013      0.218      0.222      0.286      0.775        Ellid, 2014      Post-treatment      0.030      0.040      0.040      0.023      0.865      0.776        Gryczynski, 2016      Post-treatment      0.307      0.049      0.033      1.240      2.074      0.038        Lee, 2010      Post-treatment      0.167      0.028      0.081      0.574      1.475      0.140      0.58      0.774        Rocke, 2013      Post-treatment      0.127      0.012      0.218      0.774      1.475      0.140      0.539      0.040      0.528      0.796        Condersma, 2011      Post-treatment      0.126      0.131 <td< td=""><td>Study name</td><td></td><td>Stati</td><td>stics for eac</td><td>h study</td><td></td><td></td><td></td><td>Н</td><td>Iedges'</td><td>'s g and 95</td><td>% CI</td><td></td><td></td></td<>	Study name		Stati	stics for eac	h study				Н	Iedges'	's g and 95	% CI				
Becker, 2014a Becker, 2014b Becker, 2014b Becker, 2014b Becker, 2014b Besker, 2014b Besker, 2014b Besker, 2014b Besker, 2014b Besker, 2014b Besker, 2014b Besker, 2014b Besker, 2015b Jonas, 2012 Post-treatment 0.031 Jonas, 2012 Post-treatment 0.031 Jonas, 2012 Post-treatment 0.040 Ondersma, 2014 Post-treatment 0.057 Ondersma, 2010 Post-treatment 0.040 Diff, 0.028 Diff, 2015 Dest-treatment 0.040 Diff, 0.029 Diff, 2015 Schaub, 2015b Schaub, 2015b Dest-treatment 0.046 Diff, 0.028 Diff, 2016 Post-treatment 0.046 Diff, 0.028 Diff, 2017 Diff, 2018 Post-treatment 0.046 Diff, 0.028 Diff, 2018 Diff, 2014 Post-treatment 0.046 Diff, 0.028 Diff, 2013 Diff, 2014 Post-treatment 0.046 Diff, 0.028 Diff, 0.028 Diff, 2018 Diff, 2014 Post-treatment 0.046 Diff, 0.028 Diff, 0.028 Diff, 2018 Diff, 2018 Diff, 2018 Diff, 2018 Diff, 2014 Post-treatment 0.046 Diff, 0.028 Diff, 0.029 Diff, 0.000 Diff, 0.021 Diff, 0.028 Diff, 0		н	edges's	Standard		Lower	Upper									
Besker, 2014b      Post-treatment      0.000      0.167      0.028      -0.327      0.327      0.000      1.000        Christoff, 2015      Post-treatment      0.030      0.330      0.291      -0.286      0.775        Elliot, 2016      Post-treatment      0.031      0.221      0.049      -0.403      0.465      0.139      0.890        Jonas, 2012      Post-treatment      0.037      0.094      0.035      1.240      0.038      0.890        Charsma, 2012      Post-treatment      0.637      0.037      0.094      0.035      1.240      0.038        Lee, 2010      Post-treatment      0.032      0.112      0.012      0.214      0.203      0.982        Ondersma, 2014      Post-treatment      0.046      0.012      0.214      0.203      0.982        Ondersma, 2014      Post-treatment      0.046      0.174      0.030      0.300      0.288      0.774        Rooke, 2013      Post-treatment      0.046      0.176      0.318      0.312      3.315      0.001        Schaub, 2015b      Post-treatment		Assessment	g	error	Varianc	e limit	limit	Z-Valu	ue p-Value	е						
Christoff, 2015    Post-treatment 0.050    0.174    0.030    0.390    0.291    -0.286    0.775      Ellict, 2014    Post-treatment 0.031    0.212    0.013    -0.188    0.252    0.284    0.776      Gryczynski, 2016    Post-treatment 0.031    0.221    0.049    0.030    -0.280    0.170    -1.260    0.208      Kay-Lambkin, 2009    Post-treatment 0.637    0.307    0.094    0.031    1.240    2.074    0.038      Condersma, 2007    Post-treatment 0.022    0.108    0.012    -0.214    0.209    -0.023    0.882      Condersma, 2007    Post-treatment 0.414    0.199    0.040    0.024    0.804    2.081    0.037      Ondersma, 2014    Post-treatment 0.246    0.167    0.032    -0.480    0.258    0.774      Rooke, 2013    Post-treatment 0.196    0.017    0.031    -0.300    0.311    2.288    0.706      Tossman, 2011    Post-treatment 0.196    0.059    0.004    0.001    0.001    0.001    0.001    0.001      Valton, 2012    Follow-up    0.488    0.012	Becker, 2014a	Post-treatment	0.000	0.164	0.027	-0.321	0.321	0.000	1.000	1	1		<u> </u>	1		
Elliot, 2014 Post-treatment 0.032 0.112 0.013 -0.188 0.252 0.284 0.776 Gryczynski, 2016 Post-treatment 0.036 0.221 0.049 -0.403 0.465 0.139 0.890 Jonas, 2012 Post-treatment 0.366 0.243 0.059 0.782 0.170 -1.260 0.208 Kay-Lambkin, 2009 Post-treatment 0.637 0.307 0.094 0.035 1.240 2.074 0.038 Lee, 2010 Post-treatment 0.414 0.109 0.040 0.024 0.804 2.081 0.037 Ondersma, 2017 Post-treatment 0.246 0.167 0.028 -0.081 0.574 1.475 0.140 Palfai, 2014 Post-treatment 0.322 0.179 0.032 -0.403 0.300 -0.238 0.774 Rooke, 2013 Post-treatment 0.166 0.173 0.030 -0.233 0.446 0.614 0.539 Schaub, 2015b Post-treatment 0.166 0.173 0.030 -0.233 0.446 0.614 0.539 Schaub, 2015b Post-treatment 0.166 0.173 0.030 0.391 0.228 0.796 Tossman, 2011 Post-treatment 0.196 0.059 0.004 0.080 0.312 3.315 0.001 Towe, 2014 Post-treatment 0.196 0.059 0.004 0.080 0.312 3.315 0.001 Malton, 2013 Post-treatment 0.196 0.059 0.004 0.080 0.312 3.315 0.001 Gryczynski, 2016 Follow-up 0.164 0.167 0.028 0.174 0.434 0.000 1.000 Jonas, 2012 Follow-up 0.154 0.167 0.028 0.178 1.511 2.844 0.004 Lee, 2010 Follow-up 0.154 0.167 0.028 0.178 1.511 2.844 0.004 Lee, 2010 Follow-up 0.068 0.108 0.012 0.288 0.747 Kay-Lambkin, 2009Follow-up 0.895 0.315 0.099 0.278 1.511 2.844 0.004 Lee, 2010 Follow-up 0.056 0.138 0.012 0.288 0.144 -0.627 0.531 Cndersma, 2014 Follow-up 0.154 0.167 0.028 0.172 0.354 POOLED 0.158 0.013 0.018 0.107 0.627 0.531 Cndersma, 2014 Follow-up 0.367 0.133 0.018 0.107 0.627 0.531 Cndersma, 2014 Follow-up 0.367 0.133 0.018 0.107 0.627 0.531 Cndersma, 2014 Follow-up 0.353 0.221 0.049 -0.079 0.785 1.600 0.110 Walton, 2013 Follow-up 0.353 0.221 0.049 -0.079 0.785 1.600 0.110 Walton, 2013 Follow-up 0.353 0.221 0.049 -0.079 0.785 1.600 0.110 Walton, 2013 Follow-up 0.353 0.221 0.049 -0.079 0.785 1.600 0.110 Walton, 2013 Follow-up 0.353 0.221 0.049 -0.079 0.785 1.600 0.110 Walton, 2013 Follow-up 0.353 0.221 0.049 -0.079 0.785 1.600 0.110 Walton, 2013 Follow-up 0.353 0.221 0.049 -0.079 0.785 1.600 0.110 Walton, 2013 Follow-up 0.356 0.138 0	Becker, 2014b	Post-treatment	0.000	0.167	0.028	-0.327	0.327	0.000	1.000				_			
Gryczynski, 2016    Post-treatment 0.031    0.221    0.049    -0.403    0.465    0.139    0.890      Jonas, 2012    Post-treatment 0.306    0.243    0.059    -0.782    0.170    -1.200    0.208      Kay-Lambkin, 2009    Post-treatment 0.637    0.074    0.030    -0.640    0.033    0.465    0.120    0.008      Condersma, 2017    Post-treatment 0.414    0.199    0.040    0.024    0.804    2.081    0.037      Ondersma, 2014    Post-treatment 0.446    0.167    0.028    -0.081    0.574    1.475    0.140      Schaub, 2015a    Post-treatment 0.382    0.133    0.018    0.121    0.642    2.875    0.004      Schaub, 2015a    Post-treatment 0.046    0.176    0.031    -0.300    0.312    3.315    0.001      Toske, 2011    Post-treatment 0.046    0.176    0.031    0.228    0.774    0.766    0.685    0.493      Schaub, 2015b    Post-treatment 0.046    0.176    0.058    0.312    3.315    0.001    0.021    0.049    0.028    0.547    0.531    0.244<	Christoff, 2015	Post-treatment	-0.050	0.174	0.030	-0.390	0.291	-0.286	0.775				-			
Jonas, 2012    Post-treatment 0.306    0.243    0.059    -0.782    0.170    -1.260    0.208      Kay-Lambkin, 2009/Post-treatment 0.637    0.307    0.094    0.035    1.240    2.074    0.038      Lee, 2010    Post-treatment 0.414    0.199    0.040    0.024    0.804    2.081    0.037      Ondersma, 2017    Post-treatment 0.144    0.199    0.040    0.024    0.804    2.081    0.037      Ondersma, 2014    Post-treatment 0.382    0.167    0.028    -0.081    0.574    1.475    0.140      Palfai, 2014    Post-treatment 0.382    0.179    0.032    -0.403    0.300    -0.288    0.774      Rooke, 2013    Post-treatment 0.382    0.173    0.030    -0.233    0.446    0.614    0.539      Schaub, 2015a    Post-treatment 0.196    0.059    0.004    0.080    0.312    3.315    0.001      Towe, 2014    Post-treatment 0.735    0.226    0.051    0.292    0.137    0.232    0.441    0.021      Malton, 2012    Follow-up    0.166    0.179    0.328    0.1																
Kay-Lambkin, 2009Post-treatment 0.637    0.307    0.094    0.035    1.240    2.074    0.038      Lee, 2010    Post-treatment-0.002    0.108    0.012    -0.214    0.209    -0.023    0.982      Ondersma, 2017    Post-treatment 0.144    0.199    0.040    0.024    0.804    2.081    0.037      Ondersma, 2014    Post-treatment 0.046    0.167    0.028    -0.023    0.982      Schaub, 2015a    Post-treatment 0.046    0.176    0.031    -0.030    -0.238    0.774      Schaub, 2015b    Post-treatment 0.046    0.176    0.031    -0.300    0.391    0.258    0.796      Toses, 2014    Post-treatment 0.735    0.226    0.051    0.292    1.178    3.249    0.001      Walton, 2013    Post-treatment 0.735    0.226    0.174    0.032    -0.403    0.300    1.201    0.021      Gryczynski, 2016    Follow-up    0.116    0.059    0.003    0.117    0.215    2.301    0.021      Jonas, 2012    Follow-up    0.068    0.108    0.122    0.280    0.144    0.027 </td <td></td>																
Lee, 2010 Ordersma, 2007 Post-treatment 0,002 Ordersma, 2014 Post-treatment 0,246 Ordersma, 2014 Post-treatment 0,246 Ordersma, 2014 Post-treatment 0,246 Ordersma, 2014 Post-treatment 0,246 Ordersma, 2013 Schaub, 2015b Post-treatment 0,166 Ordersma, 2014 Post-treatment 0,062 Ordersma, 2015 Post-treatment 0,066 Ordersma, 2014 Post-treatment 0,066 Ordersma, 2014 Post-treatment 0,066 Ordersma, 2014 Post-treatment 0,075 Ordersma, 2017 Gryczynski, 2016 Gryczynski, 2016 Follow-up PoolED Ordersma, 2014 Post-treatment 0,000 Ordersma, 2014 Post-treatment 0,000 Ordersma, 2014 Post-treatment 0,000 Ordersma, 2014 Post-treatment 0,000 Ordersma, 2014 Post-treatment 0,000 Ordersma, 2014 Post-treatment 0,016 Ordersma, 2014 PoloLED Ordersma, 2014 PoloLED Ordersma, 2014 PoloLED Ordersma, 2013 PoOLED Ordersma, 2014 PoloLED Ordersma, 2014 Polow-up Ordersma,																
Ondersma, 2007      Post-treatment      0.414      0.199      0.040      0.024      0.804      2.081      0.037        Ondersma, 2014      Post-treatment      0.246      0.167      0.022      -0.081      0.574      1.475      0.140        Palfai, 2014      Post-treatment      0.322      0.133      0.018      0.121      0.642      2.875      0.004        Schaub, 2015a      Post-treatment      0.166      0.173      0.030      -0.233      0.446      0.614      0.539        Schaub, 2015b      Post-treatment      0.166      0.176      0.031      -0.300      0.391      0.258      0.796        Towe, 2014      Post-treatment      0.166      0.176      0.031      -0.300      0.391      0.258      0.796        Walton, 2013      Post-treatment      0.196      0.326      0.212      1.178      3.249      0.001        Jomas, 2012      Follow-up      0.106      0.221      0.049      0.434      0.434      0.000      1.000        Jomas, 2012      Follow-up      0.166      0.179      0.228<																
Ondersma, 2014      Post-treatment 0.246      0.167      0.028      -0.081      0.574      1.475      0.140        Palfai, 2014      Post-treatment -0.052      0.179      0.032      -0.403      0.300      -0.288      0.774        Rooke, 2013      Post-treatment 0.382      0.133      0.018      0.121      0.642      2.875      0.004        Schaub, 2015b      Post-treatment 0.066      0.176      0.031      -0.300      0.391      0.258      0.796        Tossman, 2011      Post-treatment 0.196      0.059      0.004      0.800      0.312      3.315      0.001        Walton, 2013      Post-treatment 0.196      0.059      0.004      0.802      0.633      0.547        Malton, 2013      Post-treatment 0.196      0.059      0.004      0.802      0.633      0.547        Malton, 2013      Post-treatment 0.046      0.138      0.019      0.238      0.620      0.603      0.547        Kay-Lambkin, 2009Follow-up      0.166      0.179      0.028      0.172      0.786      0.606      0.110        Macke, 2010      Follow-u	,															
Palfai, 2014    Post-treatment -0.052    0.179    0.032    -0.403    0.300    -0.288    0.774      Rooke, 2013    Post-treatment 0.382    0.133    0.018    0.121    0.642    2.875    0.004      Schaub, 2015a    Post-treatment 0.106    0.173    0.030    -0.233    0.446    0.614    0.539      Schaub, 2015b    Post-treatment 0.106    0.176    0.031    -0.300    0.391    0.258    0.796      Tossman, 2011    Post-treatment 0.196    0.059    0.004    0.080    0.312    3.315    0.001      Walton, 2013    Post-treatment-0.094    0.138    0.019    -0.364    0.176    -0.685    0.493      POOLED    0.116    0.050    0.003    0.017    0.215    2.301    0.021      Gryczynski, 2016    Follow-up    0.146    0.242    0.058    -0.328    0.620    0.603    0.547      Kay-Lambkin, 2009Follow-up    0.895    0.315    0.099    0.278    1.511    2.844    0.004      Lee, 2010    Follow-up    0.068    0.108    0.107    0.627 <t< td=""><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>_</td></t<>														_		
Rooke, 2013 Schaub, 2015a      Post-treatment 0.382      0.133      0.018      0.121      0.642      2.875      0.004        Schaub, 2015a      Post-treatment 0.106      0.173      0.030      -0.233      0.446      0.614      0.539        Schaub, 2015b      Post-treatment 0.046      0.176      0.031      -0.330      0.312      3.315      0.001        Tossman, 2011      Post-treatment 0.735      0.226      0.051      0.229      1.178      3.249      0.001        Towe, 2014      Post-treatment-0.094      0.138      0.019      -0.364      0.176      -0.685      0.493        POOLED      0.116      0.050      0.003      0.017      0.215      2.301      0.021        Gryczynski, 2016      Follow-up      0.000      0.221      0.049      -0.434      0.434      0.000      1.000        Jonas, 2012      Follow-up      0.146      0.242      0.058      -0.328      0.620      0.633      0.547        Kay-Lambkin, 2009      Follow-up      0.056      0.118      0.012      0.280      0.144      -0.627	,												_			
Schaub, 2015a    Post-treatment    0.106    0.173    0.030    -0.233    0.446    0.614    0.539      Schaub, 2015b    Post-treatment    0.046    0.176    0.031    -0.300    0.391    0.258    0.796      Tossman, 2011    Post-treatment    0.196    0.059    0.004    0.080    0.312    3.315    0.001      Towe, 2014    Post-treatment    0.735    0.226    0.051    0.222    1.178    3.249    0.001      Walton, 2013    Post-treatment    0.000    0.221    0.049    -0.364    0.176    -0.685    0.493      Yoons, 2012    Follow-up    0.106    0.050    0.003    0.017    0.215    2.301    0.021      Gryczynski, 2016    Follow-up    0.000    0.221    0.049    -0.348    0.434    0.000    1.000      Jonas, 2012    Follow-up    0.068    0.117    0.228    0.127    0.331    0.214    0.004    1.046      Lee, 2010    Follow-up    -0.068    0.167    0.022    -0.230    0.740    0.035    0.017    0.232																
Schaub, 2015b      Post-treatment      0.046      0.176      0.031      -0.300      0.391      0.258      0.796        Tossman, 2011      Post-treatment      0.196      0.059      0.004      0.080      0.312      3.315      0.001        Tossman, 2011      Post-treatment      0.735      0.226      0.051      0.292      1.178      3.249      0.001        Walton, 2013      Post-treatment      0.090      0.212      0.364      0.176      -0.685      0.493        Jonas, 2012      Follow-up      0.116      0.050      0.003      0.017      0.215      2.301      0.021        Jonas, 2012      Follow-up      0.146      0.242      0.058      -0.328      0.620      0.603      0.547        Kay-Lambkin, 2009Follow-up      0.895      0.315      0.099      0.278      1.511      2.844      0.004        Lee, 2010      Follow-up      -0.068      0.108      0.012      -0.280      0.144      -0.627      0.531        Palfai, 2014      Follow-up      0.367      0.133      0.018      0.017	,												<u> </u>			
Tossman, 2011 Towe, 2014    Post-treatment 0.196 Post-treatment 0.735    0.059 0.226    0.004    0.080    0.312    3.315    0.001      Walton, 2013    Post-treatment 0.735    0.226    0.051    0.292    1.178    3.249    0.001      Gryczynski, 2016    Follow-up    0.116    0.050    0.003    0.017    0.215    2.301    0.021      Gryczynski, 2016    Follow-up    0.000    0.221    0.049    0.434    0.434    0.000    1.000      Jonas, 2012    Follow-up    0.146    0.242    0.058    0.328    0.620    0.637    0.547      Kay-Lambkin, 2009Follow-up    0.154    0.167    0.280    0.144    -0.627    0.531      Ondersma, 2014    Follow-up    -0.060    0.179    0.032    -0.411    0.292    -0.332    0.740      Rooke, 2013    Follow-up    0.056    0.138    0.019    -0.326    0.214    -0.404    0.686      POOLED    0.138    0.019    -0.326    0.214    -0.404    0.686      POIL    0.138    0.019    -0.326    0.214 <td></td>																
Walton, 2013    Post-treatment-0.094    0.138    0.019    -0.364    0.176    -0.685    0.493      Gryczynski, 2016    Follow-up    0.000    0.221    0.049    -0.434    0.434    0.000    1.000      Jonas, 2012    Follow-up    0.146    0.242    0.058    -0.328    0.620    0.603    0.547      Kay-Lambkin, 2009    Follow-up    0.068    0.118    0.012    -0.280    0.114    -0.627    0.531      Ondersuna, 2014    Follow-up    0.056    0.133    0.018    0.017    0.627    2.766    0.006      Palfai, 2014    Follow-up    0.056    0.138    0.019    -0.326    0.214    -0.040    0.686      Towe, 2013    Follow-up    -0.056    0.138    0.019    -0.326    0.214    -0.040    0.686      POOLED    0.138    0.084    0.007    -0.278    1.640    0.100      Matton, 2013    Follow-up    0.056    0.138    0.019    -0.326    0.214    -0.040    0.686      POOLED    0.138    0.084    0.007 <t< td=""><td>Tossman, 2011</td><td>Post-treatment</td><td>0.196</td><td>0.059</td><td>0.004</td><td>0.080</td><td>0.312</td><td>3.315</td><td>0.001</td><td></td><td></td><td>· ·</td><td>-88-  </td><td></td></t<>	Tossman, 2011	Post-treatment	0.196	0.059	0.004	0.080	0.312	3.315	0.001			· ·	-88-			
POOLED      0.116      0.050      0.003      0.017      0.215      2.301      0.021        Gryczynski, 2016      Follow-up      0.000      0.221      0.049      -0.434      0.434      0.000      1.000        Jonas, 2012      Follow-up      0.146      0.242      0.058      -0.328      0.620      0.603      0.547        Kay-Lambkin, 2009Follow-up      0.895      0.315      0.099      0.278      1.511      2.844      0.004        Lee, 2010      Follow-up      -0.068      0.108      0.012      -0.280      0.144      -0.627      0.531        Ondersma, 2014      Follow-up      -0.066      0.179      0.032      -0.111      0.292      -0.332      0.740        Rooke, 2013      Follow-up      0.056      0.133      0.018      0.107      0.627      2.766      0.006        Towe, 2014      Follow-up      -0.056      0.138      0.019      -0.326      0.214      -0.404      0.686        POOLED      0.138      0.084      0.007      -0.333      1.644      0.100														<b>-</b> ■>		
Gryczynski, 2016    Follow-up    0.000    0.221    0.049    0.034    0.434    0.000    1.000      Jonas, 2012    Follow-up    0.146    0.242    0.058    -0.328    0.620    0.603    0.547      Kay-Lambkin, 2009Follow-up    0.895    0.315    0.099    0.278    1.511    2.844    0.004      Lee, 2010    Follow-up    -0.068    0.102    -0.280    0.144    -0.627    0.531      Ondersma, 2014    Follow-up    -0.060    0.179    0.032    -0.411    0.292    -0.332    0.740      Rooke, 2013    Follow-up    -0.650    0.138    0.019    -0.326    0.214    -0.404    0.686      POOLED    0.138    0.084    0.007    -0.27    0.303    1.644    0.100	Walton, 2013												-			
Glyczyński 2010    Follow-up    0.146    0.242    0.058    -0.328    0.620    0.603    0.547      Jonas 2012    Follow-up    0.895    0.315    0.099    0.278    1.511    2.844    0.004      Lee, 2010    Follow-up    -0.068    0.108    0.012    -0.280    0.144    -0.627    0.531      Ondersma, 2014    Follow-up    -0.060    0.179    0.032    -0.411    0.292    -0.332    0.740      Rooke, 2013    Follow-up    0.367    0.133    0.018    0.107    0.627    2.766    0.006      Towe, 2014    Follow-up    0.353    0.221    0.049    -0.079    0.785    1.600    0.110      Walton, 2013    Follow-up    -0.056    0.138    0.019    -0.326    0.214    -0.404    0.686      POOLED    0.138    0.084    0.007    -0.27    0.303    1.644    0.100		POOLED	0.116	0.050	0.003	0.017	0.215	2.301	0.021							
Jonas, 2012 Follow-up Kay-Lambkin, 2009Follow-up Lee, 2010 Follow-up Palfai, 2014 Follow-up Rooke, 2013 Follow-up Walton, 2013 Follow-up OOLED 0.138 0.084 0.007 -0.027 0.303 1.644 0.100 -1.00 -0.50 0.00 0.50 1.00	Gryczynski 2016	Follow-up	0.000	0.221	0.049	-0.434	0.434	0.000	1.000							
Kay-Lambkin, 2009Follow-up    0.895    0.315    0.099    0.278    1.511    2.844    0.004      Lee, 2010    Follow-up    -0.068    0.108    0.012    -0.280    0.144    -0.627    0.531      Ondersma, 2014    Follow-up    0.154    0.167    0.028    -0.172    0.481    0.927    0.354      Palfai, 2014    Follow-up    0.060    0.179    0.032    -0.411    0.292    -0.332    0.740      Rooke, 2013    Follow-up    0.367    0.133    0.018    0.107    0.627    2.766    0.006      Towe, 2014    Follow-up    0.353    0.221    0.049    -0.079    0.785    1.600    0.110      Walton, 2013    Follow-up    -0.056    0.138    0.019    -0.326    0.214    -0.404    0.686      POOLED    0.138    0.084    0.007    -0.027    0.303    1.644    0.100		Follow-up	0.146	0.242	0.058	-0.328	0.620	0.603	0.547				▰┿			
Lee, 2010 Ondersma, 2014 Palfai, 2014 Rooke, 2013 Towe, 2014 Walton, 2013 POOLED Ondersma, 2014 Follow-up Follow	,	-	0.895	0.315	0.099	0.278	1.511	2.844	0.004					>		
Ondersma, 2014    Follow-up    0.154    0.167    0.028    -0.172    0.481    0.927    0.354      Palfai, 2014    Follow-up    -0.060    0.179    0.032    -0.411    0.292    -0.332    0.740      Rooke, 2013    Follow-up    0.367    0.133    0.018    0.107    0.627    2.766    0.006      Towe, 2014    Follow-up    0.353    0.221    0.049    -0.079    0.785    1.600    0.110      Walton, 2013    Follow-up    -0.056    0.138    0.019    -0.326    0.214    -0.404    0.686      POOLED    0.138    0.084    0.007    -0.027    0.303    1.644    0.100			-0.068	0.108	0.012	-0.280	0.144	-0.627	0.531				-			
Palfai, 2014 Rooke, 2013 Towe, 2014 Walton, 2013 PolDeeD 0.138 0.084 0.007 -0.027 0.303 1.644 0.100 POOLED 0.138 0.084 0.007 -0.027 0.303 1.644 0.100 -1.00 -0.50 0.00 0.50 1.00			0.154	0.167	0.028	-0.172	0.481	0.927	0.354							
Follow-up    Rooke, 2013    Follow-up    0.367    0.133    0.018    0.107    0.627    2.766    0.006      Towe, 2014    Follow-up    0.353    0.221    0.049    -0.079    0.785    1.600    0.110      Walton, 2013    Follow-up    -0.056    0.138    0.019    -0.326    0.214    -0.404    0.686      POOLED    0.138    0.084    0.007    -0.027    0.303    1.644    0.100	,												<u> </u>			
Rook, 2013    Follow-up    0.353    0.221    0.049    -0.079    0.785    1.600    0.110      Towe, 2014    Follow-up    -0.056    0.138    0.019    -0.326    0.214    -0.0404    0.686      Walton, 2013    POOLED    0.138    0.084    0.007    -0.027    0.303    1.644    0.100		Follow-up											<b></b>			
Walton, 2013    Follow-up POOLED    0.056    0.138    0.019    0.0326    0.214    -0.404    0.686      POOLED    0.138    0.084    0.007    -0.027    0.303    1.644    0.100		Follow-up										-+-		_		
POOLED 0.138 0.084 0.007 -0.027 0.303 1.644 0.100 -1.00 -0.50 0.00 0.50 1.00		Follow-up		0.138	0.019	-0.326		-0.404	0.686				_			
	matton, 2013	POOLED		0.084												
										-1.0	005	0.00	0.50	1.00		
										2.0		-				

Boumparis N, Loheide-Niesmann L, Blankers M, Ebert DD, Korf D, Schaub MP, et al. Short- and long-term effects of digital prevention and treatment interventions for cannabis use reduction: A systematic review and meta-analysis. Drug Alcohol Depend. 2019 Jul 1;200:82-94.



# 2018 Review and Meta-analysis of 30 Studies for Cannabis (*Cont.*)

- Outcomes (continued):
  - Subgroup analyses did not show significant differences between groups like number of sessions, recruitment strategy/location, guided/unguided, intervention type
  - Trends support multi-session interventions, such as those combining CBT with MI
- Take home
  - While quality effect sizes are low, because of the impact on prevention and potentially reaching a large number of people, there is promise.
  - Need more research with randomization/blinding

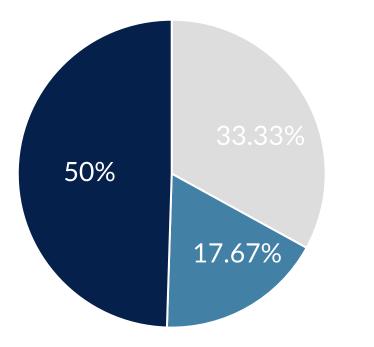


#### 2017 Systematic Review of 17 Studies Internet Interventions for Illicit Drug Use

- Compare to TAU, MI, brief intervention or psychoeducation
- 9 added to guided care
- Approaches included CRA largely for opioids, and CBT for stimulants
- Effect of intervention was mildly significant (Hedge's g =0.301, p<0.001). (No benefit for stimulant)
- More effective:
  - Guided interventions
  - Validated outcomes (toxicology) versus self-report
  - Clinic-based technology was also more effective than school or home.
- Take home: Effectiveness was small but promising and more research is needed



#### 2021 Review of Smoking Cessation Apps (Some Guided)

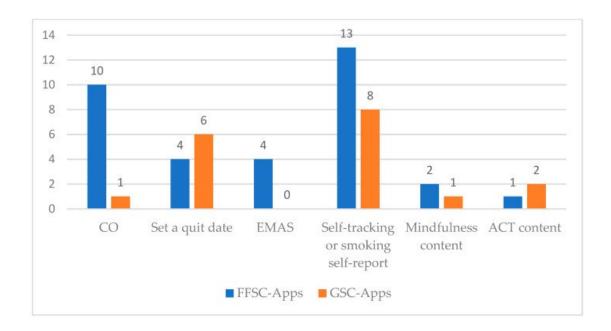


- Better Results in the Experimental Condition
- Better Results in the Control Condition
- No Significant Differences Between Conditions

- Initial scope: 6016 studies → narrowing to 24 apps
- Only 8 studies reported significant differences between treatment and other intervention
- Only 6 were considered high quality studies (image shows their outcomes)
- Some apps were just as effective as the control groups (self-help material, text messaging service, before/after)



# 2021 Review of Smoking Cessation Apps (Some Guided, *Cont.*)

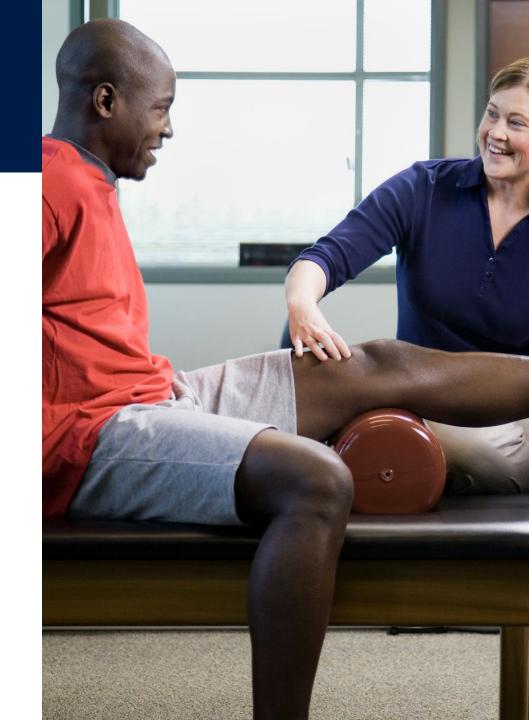


- Most studies did not describe their apps well, mentioned in several other reviews; authors extracted data in image
- 7 of the studies targeted more complex groups (dual diagnosis, unhoused)
- Several studies were pilots (small n)
- Take home:
  - Especially for stand-alone apps, opportunity to at least function as good as no intervention since smoking undertreated



#### Not Included in this Presentation

- Not discussed are parallel areas of substance use disorders
- Examples:
  - Pain management
  - Overdose surveillance through technology





# Technology to Deliver Standard Care Like Telemedicine



### Telemedicine

- Prior to the pandemic from the VHA showed that tele-buprenorphine increased and later that treatment discontinuation from buprenorphine was lower for the telemedicine group
- COVID-19:
  - Prior to the pandemic, less than 1% of mental health and SUD outpatient care was via telehealth based on national data
  - Increased to 40% of mental health and substance use outpatient visits and 11% of other visits (during the March- August 2020 period)

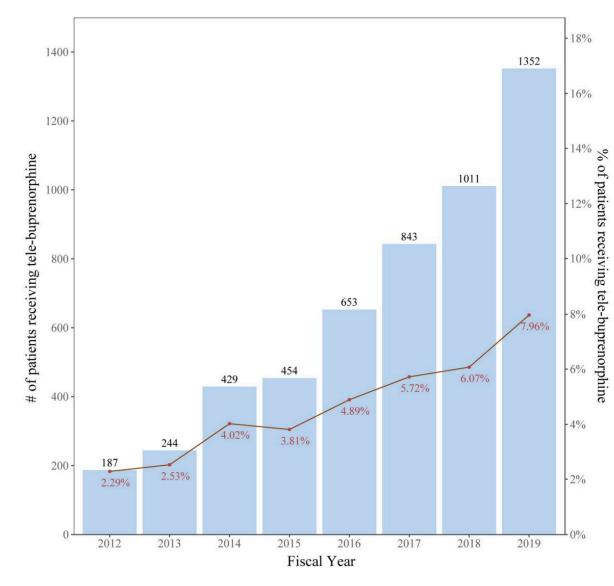
Lo J, Panchal N, Mar 15 BFMP, 2022. Telehealth Has Played an Outsized Role Meeting Mental Health Needs During the COVID-19 Pandemic [Internet]. KFF. 2022 [cited 2022 Aug 11]. Available from: https://www.kff.org/coronavirus-covid-19/issue-brief/telehealth-has-played-an-outsized-role-meeting-mental-health-needs-during-the-covid-19-pandemic/



Lin LA, Fortney JC, Bohnert ASB, Coughlin LN, Zhang L, Piette JD. Comparing telemedicine to in-person buprenorphine treatment in U.S. veterans with opioid use disorder. J Subst Abuse Treat. 2022 Feb;133:108492.

Vakkalanka JP, Lund BC, Ward MM, Arndt S, Field RW, Charlton M, et al. Telehealth Utilization Is Associated with Lower Risk of Discontinuation of Buprenorphine: a Retrospective Cohort Study of US Veterans. J Gen Intern Med. 2022 May;37(7):1610–8.

### Telemedicine

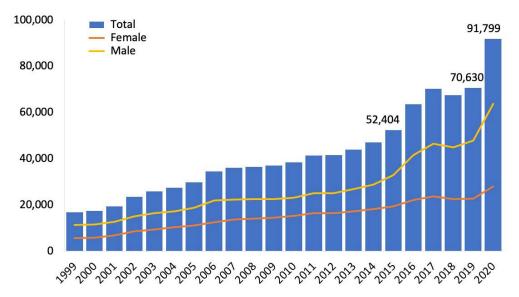






#### Federal Restrictions on MOUD Were Present During the Pandemic

#### Figure 1. National Drug-Involved Overdose Deaths\* Number Among All Ages, by Gender, 1999-2020



\*Includes deaths with underlying causes of unintentional drug poisoning (X40–X44), suicide drug poisoning (X60–X64), homicide drug poisoning (X85), or drug poisoning of undetermined intent (Y10–Y14), as coded in the International Classification of Diseases, 10th Revision. Source: Centers for Disease Control and Prevention, National Center for Health Statistics. Multiple Cause of Death 1999-2020 on CDC WONDER Online Database, released 12/2021.

- SAMHSA granting flexibility for OTPs with 28-day supply of take-homes (14 days for less stable patients)
- DEA waived the in-person requirement for buprenorphine via telemedicine
- Unfortunately, despite all of this, from 2019 to 2020, overdose rates increased by 30% and again by 15% in 2021



#### Review of 25 Innovation Studies on Treating OUD During COVID-19

- 16 studies included telemedicine as an innovation
  - Basic video or phone sessions for care
  - Distributing phones to help patient with limited access
  - Building sanitized phone booths
- Naloxone education online
  - Text messaging to connect to young people
  - Virtual groups
- On take-home dosing increasing
  - Variation in use of those relaxed regulations
- Other challenges have to do with technology access, toxicology testing



# ATA and APA Best Practices for Video Telehealth

- Recommendations from administrative issues, legal and regulatory, emergencies, technical considerations, clinical considerations and special populations (e.g., child/adolescent)
- For SUD specifically they review assessment, testing and subsequent visits
  - Buprenorphine prescribing
- Acknowledge that telehealth reimbursement is a topic to consider when there are parity discussions
- Regardless of regulatory changes (for example SAMHSA proposed rule) telehealth is expanding and all health care providers must be versed in the delivery



# 2019 Review of Telemedicine for SUD (Medications and Therapy)

- 13 publications about 12 studies, including 7 RCTs
- Tobacco (n=3 therapy+meds), alcohol (n=5 and therapy only) and opioid (n=5 therapy+methadone or buprenorphine)
- Studies with comparison groups didn't find differences in outcomes compared to in person or phone or usual care
  - But noticeable effects on retention
  - AND high satisfaction with telemedicine
- Based on results, reviewers cannot recommend telemedicine over conventional treatments, but in resource strained places where evidence-based treatments are not readily available, telemedicine is promising



# Emerging Areas

Social Media Chatbots Peer Support/Groups Wearables Virtual Reality





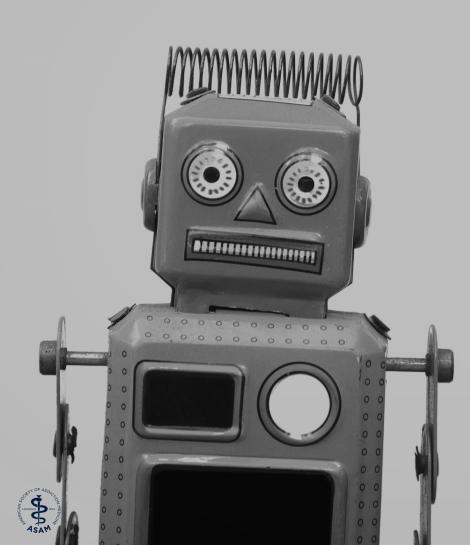
# Social Media

- Often cited as a negative influence on mental health, it can do good from a survey of hazardous drinking adults who use social media
  - Exposure to peer pro-drinking posts was negatively associated with intentions to seek treatment
  - Exposure to peer alcohol-related negative consequences posts AND peer posts about positive experiences with treatment/recovery were positively associated with treatment-seeking intention
- TikTok is a platform of brief videos by user and has potential for wide reach
  - Study examined 82 of the most liked TikTok videos related to attempts to cut down on or abstain from substances and/or strengthen SUD recovery
  - Videos had 2 million views and 325,000 "likes" on average;
  - Shared themes of a journey from active SUD to recovery, recovery milestones and relapses



# Social Media (Cont.)

- 2018 review on social media interventions for smoking cessation identified seven studies between 2014 and 2018 (n=9755) using Facebook (n=4) and Twitter (n=2)
  - Tailored content, targeted reminders and moderated discussions
  - Often treatment groups smoked less at follow up
  - Active participation (comments, likes) associated with improved outcomes
  - Retention in the studies range from 35% to 84% in one month to one-year studies
- Still need future rigorous trials are necessary to establish effectiveness, evaluate the costs/ sustainability of these programs, and determine whether these programs can reach vulnerable populations who smoke more



# Chatbots

- Chatbot: software or hardware that can converse with users without a human facilitator using machine learning and artificial intelligence
- Bots tend to provide warm and friendly messages based on user, similar to reflections in motivational interviewing
- 2019 QUALITATIVE review describes 14 early chatbots in mental health
  - None for SUD
  - One focused on healthy lifestyle in women (n=61) which did help users significantly decrease alcohol consumption
- Research has not been sufficient for review data

# Digital Peer Support

- Cochrane Review demonstrated TSF was more effective than other established treatments, such as CBT, for increasing abstinence (2020)
- Digital options in pandemic grew
- May be more challenging to complete elements of TSF (finding a sponsor, disclosure, picking up on cues) via video
- Challenges around access to technology and privacy, especially for groups that have "anonymity"



Bergman BG, Kelly JF. Online digital recovery support services: An overview of the science and their potential to help individuals with substance use disorder during COVID-19 and beyond. J Subst Abuse Treat. 2021 Jan;120:108152.



# Digital Peer Support (Cont.)

- A summary of early guidance on virtual peer support notes organizations with compiled lists of free, socialonline links with include, but are not limited to (reference below):
  - The Grayken Center for Addiction at the Boston Medical Center (https://www.bmc.org/addiction/covid-19-recovery-resources)
  - The American Society of Addiction Medicine (https://www.asam.org/Quality-Science/covid-19-coronavirus/support-group)
  - The National Institute on Drug Abuse (https://www-drugabuse-gov /related-topics/covid-19-resources)
  - Google's Recover Together (https://recovertogether.withgoogle.com/)
  - The Recovery Research Institute (https://www.recoveryanswers.org/media/digital-recovery-support-online-andmobile-resources/)
- (Area with little research is aftercare and IOP via telemedicine)



Bergman BG, Kelly JF. Online digital recovery support services: An overview of the science and their potential to help individuals with substance use disorder during COVID-19 and beyond. J Subst Abuse Treat. 2021 Jan;120:108152.





# Wearables and Tracking

- Systematic review of 32 studies on transdermal alcohol sensors (like SCRAM)
  - Found lack of consistency with respect to accuracy
  - Comparisons were not possible due to flaws in the studies
- Mobile phone for digital phenotyping (AKA behavioral sensing)
  - Use passively collected, real-time data from a mobile phone (e.g., GPS tracking, social patterns, typing patterns)
  - Inform assessment, predict changes in clinical status, and deliver on-demand interventions
  - Can help with relapse prevention and intervention (for example when a person is close to a triggering location like bar), or detect relapse, for example with a smartwatch detecting heart rate, detect overdose risk and more

Brobbin E, Deluca P, Hemrage S, Drummond C. Accuracy of Wearable Transdermal Alcohol Sensors: Systematic Review. J Med Internet Res. 2022 Apr 14;24(4):e35178. Mohr DC, Shilton K, Hotopf M. Digital phenotyping, behavioral sensing, or personal sensing: names and transparency in the digital age. NPJ Digit Med. 2020;3:45.

# Virtual Reality

- Computer-generated simulation of a three-dimensional environment using social equipment such as head mounted displaces (HMD)
- Exposure therapy is foundation and in SUD, show trigger and work to not using
- 2021 systematic review of 19 studies
  - Treatment studies: Participants were exposed to cues like a lighter or a cigarette in a typical virtual environment like a café with visual, auditory, olfactory, haptic stimuli
  - Craving outcome: 4 found null results, 2 reported negative results, 5 found reduction in craving
  - Use outcome: 6 reported reductions, 2 found no change, 2 found increased use and 1 was mixed.
  - Low quality
  - Conclusion: Future research should correct methodological shortcomings of existing studies through scientific rigor, including better pre-registered outcomes, investigating severity of SUD, accounting for multiple interventions and testing in representative clinical populations.
- VR is too early for widespread clinical implementation.
- Adjacent area is gamification which needs more research



# Summary

- As noted, presentation attempted to capture the current transitory state of the field.
- Next 5-10 years will yield future reviews and evidence.
- We must still use evidence based and proven methods while approaching technology with cautious optimism.





## Integrating Digital Approaches for SUD Treatment into Practice

Presented by MARIO SAN BARTOLOME, MD, FASAM



#### Use Case Example



*32-year-old female* with a 5-year history of opioid use disorder recently started on sublingual buprenorphine-naloxone. She attends your clinic to access Medication for Opioid Use Disorder and occasionally attends a Narcotics Anonymous meeting in her community.

- Medication +
- Cognitive Behavioral Therapy +
- Community Reinforcement Approach

Pairing skills training to encourage behavioral change with non-drug incentives that reinforce positive behaviors.





### Ethics, Safety, and Data Privacy

- Standards
- FDA
- Personal Health
  Information

### Industry Core Principles of Digital Therapeutics

- Prevent, manage, or treat a medical disorder or disease.
- Produce a medical intervention that is driven by software.
- Incorporate design, manufacture, and quality best practices
- Engage end users in product development and usability processes
- Incorporate patient privacy and security protections

- Apply product deployment, management, and maintenance best practices.
- Publish trial results inclusive of clinicallymeaningful outcomes in peer-reviewed journals.
- Be reviewed and cleared or certified by regulatory bodies as required to support product claims of risk, efficacy, and intended use.
- Make claims appropriate to clinical evaluation and regulatory status.
- Collect, analyze, and apply real world evidence and/or product performance data.



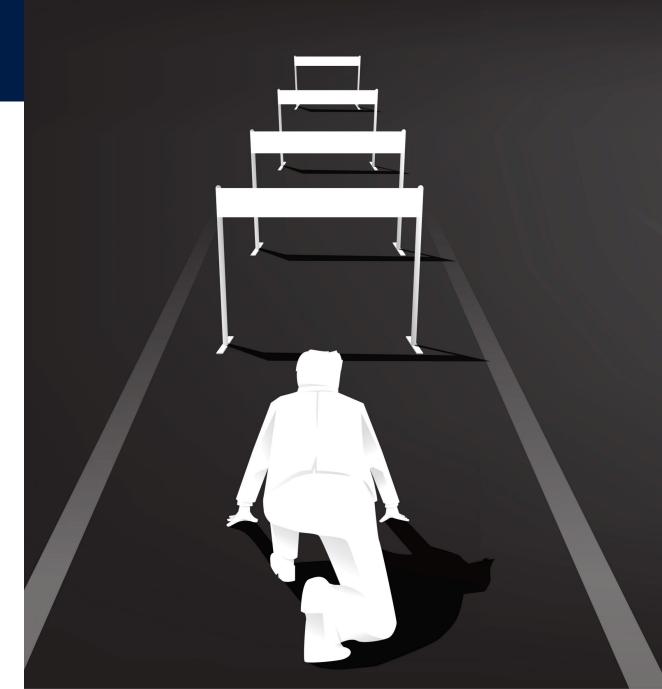
When poll is active, respond at PollEv.com/asamlearning370
 Text ASAMLEARNING370 to 22333 once to join

In a few words, please share the barriers you have encountered or expect to encounter while integrating digital approaches in SUD treatment.



### Barriers & Considerations

- Insurance coverage
- Regulation
- FDA Approval for Prescription Digital Therapeutics
- Payers
- Coding
- Organizational adoption and workflows









ASAM is committed to providing ongoing education and resources on digital approaches for substance use disorders, including advanced and specialized topics. We encourage you to stay informed and to visit our website regularly for information on upcoming webinars, courses, and other educational resources.