Manuscript *under review*

The Efficacy of Personalized Psychological Interventions in Adolescents: A Systematic Review and Meta-Analysis

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Conflicts of interest: None.

Funding: This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors.

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Abstract

Objective: We compare the efficacy of personalized psychological interventions to standardized ones for adolescents..

Method: We conducted a systematic review and meta-analysis of randomized controlled trials that compared personalized interventions with standardized interventions in adolescents Data was analyzed using Bayesian multilevel random effects meta-analysis. Eligible studies were identified through five databases; Scopus, PsychINFO, MEDLINE, Web of Science, and EMBASE. Moderation analysis was conducted to explain potential sources of effect size heterogeneity.

Results: Thirteen studies (participant $N = 2{,}569$) met inclusion criteria for the review with 10 studies ($N = 1{,}601$) providing sufficient data for inclusion in the meta-analysis. A small but significant effect size favoring personalized interventions was found ($d = 0.21$, 95%CrI [0.02, 0.39]), indicating that personalized interventions are associated with superior treatment outcomes compared to standardized interventions. Moderate between-study heterogeneity was found ($I^2 = 53.3\%$). There was no evidence of publication bias. The review also found significant variation in methods of treatment personalisation.

Conclusions: This review provides evidence that personalisation of adolescent psychological interventions is an effective way to improve treatment outcomes. Given the large number of adolescents worldwide who will experience some sort of mental health problem, personalisation could have a significantly large impact on global mental health outcomes.

Keywords: Adolescent mental health, personalized intervention, psychotherapy, meta-analysis

Public health significance:

- Personalized interventions are associated with superior treatment outcomes compared to standardized interventions in adolescents.
- A large proportion of the adolescent population could benefit from personalized intervention and these benefits may have long term-effects.
- In particular, personalizing at the component level may have the greatest benefit in treatment outcomes for adolescents.

The Efficacy of Personalized Psychological Interventions for Adolescents: A Systematic Review and Meta-Analysis

Adolescence is defined as a transitional phase from childhood to adulthood that occurs between the ages of 10 and 19 years and is characterized by rapid biological, cognitive, and social change. Studies have shown that the onset of up to 80% of mental health disorders occur before the age of 26 (Caspi et al., 2020), and that between 10 to 30% of adolescents worldwide experience a mental health problem (Keiling et al., 2011; Silva et al., 2020). During this crucial period adolescents who remain free of mental ill health have better long-term outcomes (Caspi et al., 2020). In contrast, an earlier age of onset of mental health problems is associated with an increased risk of persistent mental health disorders into adult life and a greater likelihood of developing comorbid disorders (Caspi et al., 2020).

For most mental health problems, psychological intervention is often recommended as the first-line treatment of choice for adolescents experiencing mental health problems even within the medical field (Pettitt et al., 2022). As a result, over the past five decades, clinical researchers have invested heavily in the development and evaluation of adolescent psychotherapies and there have been considerable efforts to synthesize the evidence for the efficacy of therapies. Indeed, systematic reviews have identified multiple empirically supported interventions for common mental health problems in adolescence including anxiety (Higa-McMillan et al., 2016), obsessive compulsive disorder (Freeman et al., 2014), depression (Weersing et al., 2017), attention-deficit/hyperactivity disorder (Evan et al., 2014), and conduct disorders (Kaminski & Claussen, 2017). A large meta-analysis of 447 studies spanning 30,431 adolescents synthesized 50 years of research on the efficacy of youth psychotherapies found a modest mean post-treatment effect size of only 0.46, with a 63% probability that an adolescent receiving therapy would fare better than control conditions (Weisz et al., 2017). Other meta-analyzes have identified smaller study pools that investigated the efficacy of specific adolescent interventions for particular mental health disorders and found similarly modest effect sizes. For example, meta-analyses comparing cognitive behavioral therapy (CBT) to control conditions for anxiety and for depression estimated between group pooled effect sizes of 0.45 (Baker et al., 2021) and 0.41 (Oud et al., 2019), whilst meta-analysis of 14 studies on the efficacy of acceptance and commitment therapy (ACT) for adolescent depression and anxiety found pooled post treatment effect sizes between 0.31 to 0.86 with significant between study heterogeneity ($I^2 = 82.8\%$; Fang & Ding, 2020).

What is clear from the literature is that current psychological interventions are not effective for all adolescents. Indeed, a recent meta-analysis of 40 studies on psychotherapies for adolescent depression found more than 60% of adolescents did not respond to therapy (Cuijpers et al., 2021). More worryingly it appears that efficacy of empirically supported adolescent psychotherapies is not improving or in some areas is decreasing (Weisz et al., 2019; Jones et al, 2019; Johnsen & Friborg, 2015). This is evidence by a meta-analysis of 453 studies and 31,993 adolescents spanning over 50 years which found that mean effect sizes of the efficacy of youth psychotherapies has not significantly changed over the past five decades for anxiety or ADHD, and has decreased significantly year over year for depression and conduct problems, with similar effect sizes across passive and active control groups (Weisz et al., 2019).

These findings suggest a worrying trend for clinicians and researchers alike that efforts to improve the general quality of youth psychotherapy models have not translated into improved adolescent outcomes. This pattern of stagnating or decreasing effect sizes, may to some degree, reflect an upper limit to efficacy and growth of current standardized youth psychotherapies. Consequently, there appears to be the need for new approaches to youth psychotherapy design and implementation in contrast to current methods of making small incremental changes to current psychotherapies (Weisz et al., 2019).

One such approach that is emerging in the psychological literature is personalisation (Ng & Weisz, 2016; Wright & Wood, 2020). Multiple personalisation approaches have been documented in the literature, with treatment-matching and individually tailored designs being the most common. Treatment-matching involves prospectively matching subgroups of clients to treatments based on hypothesized traits or predetermined methods (eg., machine learning algorithms, risk factors, etc.; Cohen et al., 2021). Individually tailored approaches involve tailoring treatments to individual clients based on such things as comorbidities, treatment response, or idiosyncratic case conceptualizations (Cohen et al., 2021).

Personalizing interventions is based on the hypothesis that different therapy models, strategies, or components have differing effects on individuals depending on their specific context and characteristics (Wright & Woods, 2020). There is increasing support for this hypothesis with a recent meta-analysis of clinical trials of psychotherapy for depression finding a 9% higher variance of treatment effects in intervention groups compared with control groups suggesting evidence of heterogeneity in individual responses to therapy (Kaiser et al., 2022). Recent experience sampling method studies provide further evidence of heterogeneity between individuals, with Ciarrochi et al. (2023) finding that processes that were associated with positive outcomes for some individuals were often unrelated or detrimental to others. For example, they found that although 27% of participants benefited from using the strategy of ‘doing things that had worked in the past’, a strategy considered effective at the group level, 14% actually displayed worse mental health outcomes when using this strategy (Ciarrochi et al., 2023). Similarly, Sahdra et al. (2023) found heterogeneity in how individuals relate to self-compassion and compassion for others. They found that higher compassion was associated with greater well-being in individuals who experience self-compassion and compassion for others in harmony (positive correlation), but for individuals whose compassion was not in harmony (uncorrelated or negatively correlated) higher levels of compassion were unrelated to well-being (Sahdra et al., 2023). The findings provide further support for the personalisation of interventions as there are clear differences in how different processes and strategies are associated with different outcomes of well-being for different individuals.

There has been growing interest in personalized youth psychotherapy in recent years in both treatment-matching and individually tailored approaches. For example, Hohne et al. (2023) matched adolescent refugees and asylum seekers to four different stepped care interventions based on an individual severity classification. Classification was based on individual depressive symptom severity using the Patient Health Questionnaire with adolescents displaying mild symptoms not receiving an active intervention, adolescents with moderate symptoms receiving a smartphone app developed for use with migrants and refugees, adolescents with moderate to severe symptoms receiving the START_adapt group intervention, and adolescents with severe symptoms receiving individual psychological therapy (Hohne et al., 2023). They found significant reductions in depression and PTSD symptoms with effect sizes of 0.52 and 0.27 respectively, however, found no significant differences between the treatment matched group and treatment as usual control group (Hohne et al., 2023). In contrast, Young et al. (2021) found that adolescents who were matched to either a cognitive behavior program or interpersonal program based on their psychosocial risk (high or low on cognitive and interpersonal risk) showed significantly greater decreases in depressive symptoms than adolescents who were mismatched.

In the realm of individually tailored approaches, modular youth psychotherapies, defined as psychotherapies made up of multiple self-contained and separate modules, have been growing in popularity due in part to their flexibility which facilitates personalization (Ng & Weisz, 2016). A scoping review of decision making in modular treatments for youth found that in 20 different modular youth therapies, 95% recommended using baseline assessment data to make decisions about treatment content, 65% used measurement-based care, and 25% prior research with all therapies recommending using clinical judgment (Venturo-Conerly et al., 2023). There is also evidence to suggest that modular therapies are associated with greater improvements in adolescent well-being outcomes compared to standard empirically supported treatments (Chorpita et al., 2013; Weisz et al., 2012). For example, a study comparing MATCH, a modular youth intervention, and CBT found that the modular approach outperformed CBT on improving internalizing and externalizing symptoms (Weisz et al., 2012). In the study, clinicians in the MATCH treatment group first administered modules related to the problem area defined as most important based on pretreatment assessment measures and client priorities, following this, if an interference arose (e.g., comorbidity, stressors impeding current module, etc.) then the sequence of modules was altered with other modules used systematically to address the interference (Weisz et al., 2012).

As the interest in personalisation of youth psychotherapies and interventions is relatively recent, it is yet to be fully established if such personalized psychotherapies and interventions are associated with improved adolescent treatments outcomes when compared to current standardized treatments. A systematic review of 17 studies of the efficacy of personalized psychological interventions for adults found the majority of studies reported superior treatment outcomes for personalized interventions when compared to standardized interventions and control groups (Nye et al., 2023). Further meta-analysis also revealed that personalized interventions were associated with significantly improved treatment outcomes relative to standardized interventions with a small effect size (*d* =0.22; Nye et al., 2023). Whilst this effect size is considered small by conventional standards, considering the large population of individuals who engage in psychotherapy, the findings suggest that implementing personalized interventions would still result in a substantial number of individuals experiencing improved treatment outcomes over and above current standardized treatments.

The aim of the current review was to establish the efficacy of personalized psychological interventions in adolescents using similar methods and protocols used by Nye et al. (2023) in their systematic review and meta-analysis of the efficacy of personalized psychological interventions in adults. The current review aimed to examine if personalized youth interventions are associated with improved psychological well-being and mental health outcomes compared to standardized treatments. In addition, the different methods of personalisation, such as the different ways of treatment matching and individually tailoring and how personalisation is achieved, were also investigated.

Method

The protocol for this systematic review, including plans related to the search strategy, data extractions, and analysis, was registered in the Open Science Framework (OSF) database prior to conducting the database search (https://osf.io/4cwpr/). There was a minor deviation from the protocol whereby the current review also included studies exploring interventions (personalized vs standardized) aimed at reducing risk or prevention of early onset of mental health issues in a general population of adolescents (as opposed to adolescents actively seeking treatment for a mental health issue as stated in the protocol). These studies were included on the basis that the findings of these studies contributed to answering the research question on the efficacy of personalized interventions compared to standardized interventions in improving psychological well-being and mental health in adolescents.

Search Strategy

The search was conducted in October 2023 using several databases including: PsychINFO, SCOPUS, Web of Science, MEDLINE, and Embase. Key search terms (e.g., personalization, adolescents, RCTs) were combined using Boolean operators (see Supplemental Material A). No restrictions were applied in regards to the date of publication of articles. The inclusion and exclusion criteria were based on similar criteria used by Nye et al. (2023) and altered to match the population of interest of the current review (ie., adolescents). Similarly to Nye et al. (2023), criteria were developed using a Population Intervention Comparator Outcome Study design framework (PICOS; Table 1) which has been shown to have high sensitivity and specificity compared to other search tools (Methley et al., 2014).

The first and second author screened titles, abstracts, and full texts against inclusion and exclusion criteria. Queries or disagreements were discussed between the two authors and if a decision could not be decided a third reviewer from the research team acted as an intermediary.

Table 1. PICOS framework of inclusion and exclusion criteria.

PICOS	Inclusion criteria	Exclusion criteria
Population	Adolescent clients (mean age between 10 to 19 years old).	Studies where the mean age of participants was under 10 years or over 19 years.

Intervention	Studies where participants were prospectively matched to psychological interventions, or where interventions were personalized to the individual participant.	Studies which did not prospectively match participants to interventions or personalize the intervention to the individual. Personalisation only to pharmaceutical treatments. Personalisation occurred outside of a mental health context (eg., exercise, diet).
Comparator outcome	Outcome is recorded using a validated patient reported measure, parent reported measure, or therapist reported measure. Outcome measure of a psychological construct or related to a mental health issue (eg., depression, substance use).	Outcome is not recorded using a validated patient reported measure, parent reported measure, or therapist reported measure. Outcomes measure is not for a psychological construct or related to a mental health issue (eg., smoking)
Study design	Study design is a randomized control trial with an active control group (eg., standardized	Study design is not a randomized control trial. Randomized control trial does

	interventions, supportive counseling)	not include an active control group.

Data Extraction

Data extraction was performed by the first author. The main outcomes of interest was whether personalized psychological interventions led to improved psychological well-being or mental health outcomes when compared to standardized treatments. Quantitative data pertaining to primary and secondary outcomes derived from measures of mental health symptoms of wellbeing were extracted at post intervention and follow up time points (where relevant). In addition to statistical outcomes, data related to type of personalisation, method of personalisation, mental health outcome measure used, treatment duration, treatment delivery method, treatment format, and parental involvement were extracted for use in the planned moderation analysis (Supplementary Material B).

Risk of Bias Assessment

Risk of bias assessment was conducted using the Cochrane risk-of-bias tool for randomized trials (RoB 2; Sterne et al., 2019). All included studies were rated by the first author with 50% of included studies ($k = 6$) randomly selected to and independently assessed by a second rater. Discrepancies were resolved through discussion between first and second raters. The interrater reliability was calculated using Cohen's kappa statistic, $k = 0.85$, indicating near perfect agreement between raters (McHugh, 2012).

Data Synthesis

A narrative synthesis of treatment outcomes comparing personalized and standardized interventions was conducted on all included studies. In addition, studies which provided sufficient statistical data were included in a random effects meta-analysis conducted using the *brms* package (Burkner, 2017) in R. Between group (personalized vs. standardized) effect sizes of treatment by time interactions (treatment outcomes) were calculated using the *esc* package (Ludecke, 2019) in R and converted to a common metric (Cohen's *d*) to allow for meta-analysis where needed.

Bayesian Meta-Analysis

Bayesian multilevel meta-analysis modeling (Higgins et al., 2009) was used to estimate the overall effect of the efficacy of personalized interventions compared to standardized interventions in adolescents. Bayesian meta-analysis has several advantages over traditional frequentist meta-analytic approaches including superior performance when working with smaller number of studies (Seide et al., 2019), enhanced ability to estimate between study heterogeneity and pooled effect sizes (Seide et al., 2019), and the ability to incorporate prior knowledge and assumptions using prior distributions (Harrer et al., 2021).

For meta-analysis, weakly informative priors, which incorporates weak information on the parameter that covers all possible "real-world" values, without giving any specific value too high of a probability, is recommended (Williams et al., 2018). However, when there is well-supported reason to believe that the parameter falls within a specific range of values, informative priors can be used to enhance precision without compromising accuracy (Morris et al., 2015). The current study used informative priors based on findings from the meta-analysis exploring the efficacy of personalized interventions compared to standardized interventions in adults (Nye et al., 2023) and sensitivity analysis with varying mean priors was also conducted.

When setting a prior for variance, a Half-Cauchy prior is recommended for between-study heterogeneity (τ^2) in a meta-analysis (Williams et al., 2018). In many meta-analyzes, τ (the square root of τ^2) lies somewhere around the ballpark of 0.3 (Harrer et al., 2021). Consequently, setting the Half-Cauchy prior scaling parameter to 0.3 ensures that a value of less than $\tau = 0.3$ has a 50% probability (Williams et al., 2018). However, the current study used a more conservative approach by setting the scaling parameter to 0.5 which flattens the distribution (Harrer et al., 2021).

To fit the multilevel model, an intercept-only model with random effects for effect sizes nested within studies nested within samples was specified. Effect sizes were nested within studies to account for the fact that most studies reported several effect sizes for different outcomes, and studies were nested within samples to account for the fact some studies used the same sample of adolescents.

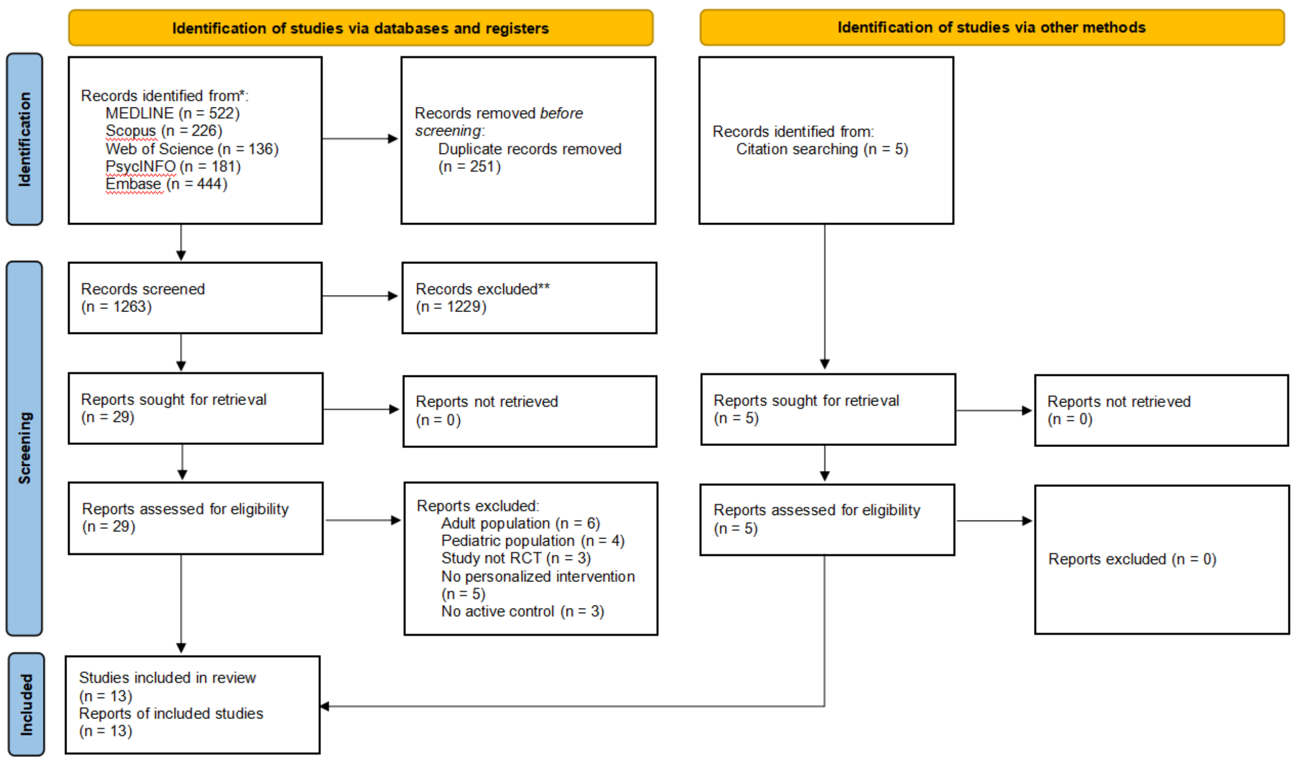
Publication bias was explored using Egger's Regression test, Funnel Plot test, and Trim and Fill method which are recommended as optimal methods of exploring publication bias for the current study's calculated population effect size and number of included studies (Fernandez-Castilla et al., 2021).

Results

In total 13 studies met the inclusion criteria. The total number of participants across all 13 studies was $N = 2{,}569$, with sample sizes ranging from eight to 996 participants. Across the 13 included studies there were eight separate samples with two studies being follow-up studies, one study using a subsample of an original sample, and three studies examining different outcomes in the same sample. The gender of participants across included studies ranged from 16% to 59% female and mean ages ranged from 10.6 to 18.6 years. Six studies personalized interventions using a treatment-matching approach and seven studies examined an individually tailored approach to personalisation of interventions. Studies that used a treatment-matching approach to personalisation allocated individuals to interventions based on drinking motives ($k = 1$), symptoms severity ($k = 1$), adolescent risk factors ($k = 3$), and an algorithm predicting response to treatment ($k = 1$). Studies that used an individually tailored approach to personalisation tailored interventions based on case conceptualisation ($k = 1$), response to parenting questionnaires ($k = 1$), adolescent risk factors ($k = 1$), and a combination of the adolescents response to treatment, comorbid problems, and emergence of treatment interfering behaviours ($k = 3$). Overall, personalisation was achieved by selecting treatment modality ($k = 4$), prescribing specific treatment modules ($k = 4$), prescribing specific strategies/exercises ($k = 1$), selecting treatment intensity ($k = 1$), and providing specific psychological feedback ($k = 3$).

Eight studies provided face to face intervention, three studies provided telehealth/online intervention, and two studies provided a combination between face to face and online/app-based interventions. Eighth studies provided interventions in an individual/one-on-one setting with a trained professional, one study provided intervention in a group setting, and four studies provided interventions in a combination of group and individual settings. Two studies provided a parent intervention aimed at improving adolescent outcomes, five studies provided interventions that involved both the adolescent and a parent, and the remaining six studies provided interventions to the adolescent only. The primary mental health issues examined across studies were: substance use ($k = 2$), trauma ($k = 1$), depression ($k = 4$), severe irritability ($k = 1$), anxiety ($k = 1$), emotional problems ($k = 1$), dependent stressors ($k = 1$), and combination of depression, anxiety, and conduct problems (k = 2). Five studies explored primary prevention interventions aimed at reducing adolescent risk and prevention of early onset of mental health issues including depression (k = 3), emotional problems (k = 1), and substance use (k =1). All included studies compared personalized treatment to standardized treatment whilst six studies also compared personalized treatment to control groups.

Figure 1. PRISMA Flow Diagram



Narrative Synthesis

Eight out of the 13 included studies found superior treatment outcomes favoring personalized interventions compared to standardized interventions. Specifically, greater reductions in internalizing and externalizing problems (k = 3), substance use (k = 2), anxiety (k = 1), depressive symptoms (k = 1), and dependent stressors (k = 1). Five studies found no significant differences between personalized and standardized interventions. Of the eight studies that reported overall superior treatment outcomes for personalized interventions, three studies found no significant differences at post-intervention but significant differences at follow-up, whilst two studies identified superior treatment outcomes for personalized interventions in only a subsample of participants. Specifically, Wurdak et al. (2016) found reduced substance and alcohol use for personalized intervention only for girls whilst Werch et al. (2010) found that personalized intervention was only associated with reduced alcohol and substance use for adolescents with a history of substance use.

Furthermore, there were only five unique samples spread across the eight studies that reported superior outcomes for personalized interventions. Specifically, three studies recruited independent and separate samples (Wurdak et al., 2016; Werch et al., 2010: Vivas-Fernandez et al., 2023), three studies recruited one independent sample (Jones et al., 2022; Jones et al., 2023; Young et al., 2021), and another two studies also recruited one independent sample (Weisz et al., 2012; Evans et al., 2020). Three of the studies that reported overall superior treatment outcomes for personalized interventions found no significant differences between personalized and standardized interventions or a slight superior treatment outcomes favoring standardized intervention at post intervention but found significant differences favoring personalized intervention at 18-month follow up (Jones et al., 2022; Jones et al., 2023; Young et al., 2021). Importantly, these three studies reported findings that pertained to the same sample of adolescents. Another study that reported superior treatment outcomes for personalized interventions at post intervention also reported six month follow up data and found that differences favoring personalized intervention were maintained at follow up (Vivas-Fernandez et al., 2023). In contrast, Weisz et al. (2012) found superior treatment outcomes for personalized intervention at post intervention but when the same sample was assessed at two year follow up in a separate study (Chorpita et al., 2013) there were no significant differences in treatment outcomes between personalized and standardized intervention. Of the five studies that found no significant differences in treatment outcomes between personlised and standardized interventions, two studies used the same sample (Yap et al., 2018) with the second study reporting 12-month follow up data that displayed similar results to the initial study (Yap et al., 2019).

Meta-Analysis

Ten studies (N = 1,601) provided sufficient data to be included in the primary meta-analysis comparing outcomes between personalized interventions versus standardized interventions. The overall mean effect size was Cohen's d = 0.21, 95%CrI [0.02, 0.39], τ(Study) = 0.17, 95%CrI [0.01, 0.48], τ(Sample) = 0.23, 95%CrI [0.03, 0.52], indicating that personalized interventions resulted in superior treatment outcomes relative to standardized interventions in adolescent populations. The overall effect size aggregated a number of mental health and psychological well-being outcomes including: depressive symptoms, anxiety symptoms, substance use behaviours, internalizing and externalizing problems, and trauma symptoms. Tests for between-study heterogeneity indicated I^2 = 53.3%, indicating the presence of moderate between-study heterogeneity (Higgins & Thompson, 2022).

Moderation analysis for the meta-analysis was conducted to investigate potential sources of heterogeneity (Table 2). Several variables including type of personalisation, mental health issue, parental involvement, how personalisation was achieved, and if the intervention was a preventative intervention were found to potentially explain a proportion of heterogeneity between treatment outcomes. Specifically, individually tailored interventions, personalized interventions targeting the adolescent only, and interventions that achieved personalisation at the component level were found to be associated with superior treatment outcomes compared to standardized interventions. Furthermore, personalized interventions were found to be associated with superior treatment outcomes in studies that used an outcomes measure of internalizing and externalizing problems, and when the intervention was not a preventative intervention (i.e., adolescents were experiencing an ongoing mental health issue).

Tabel 2. Moderation Analysis Results

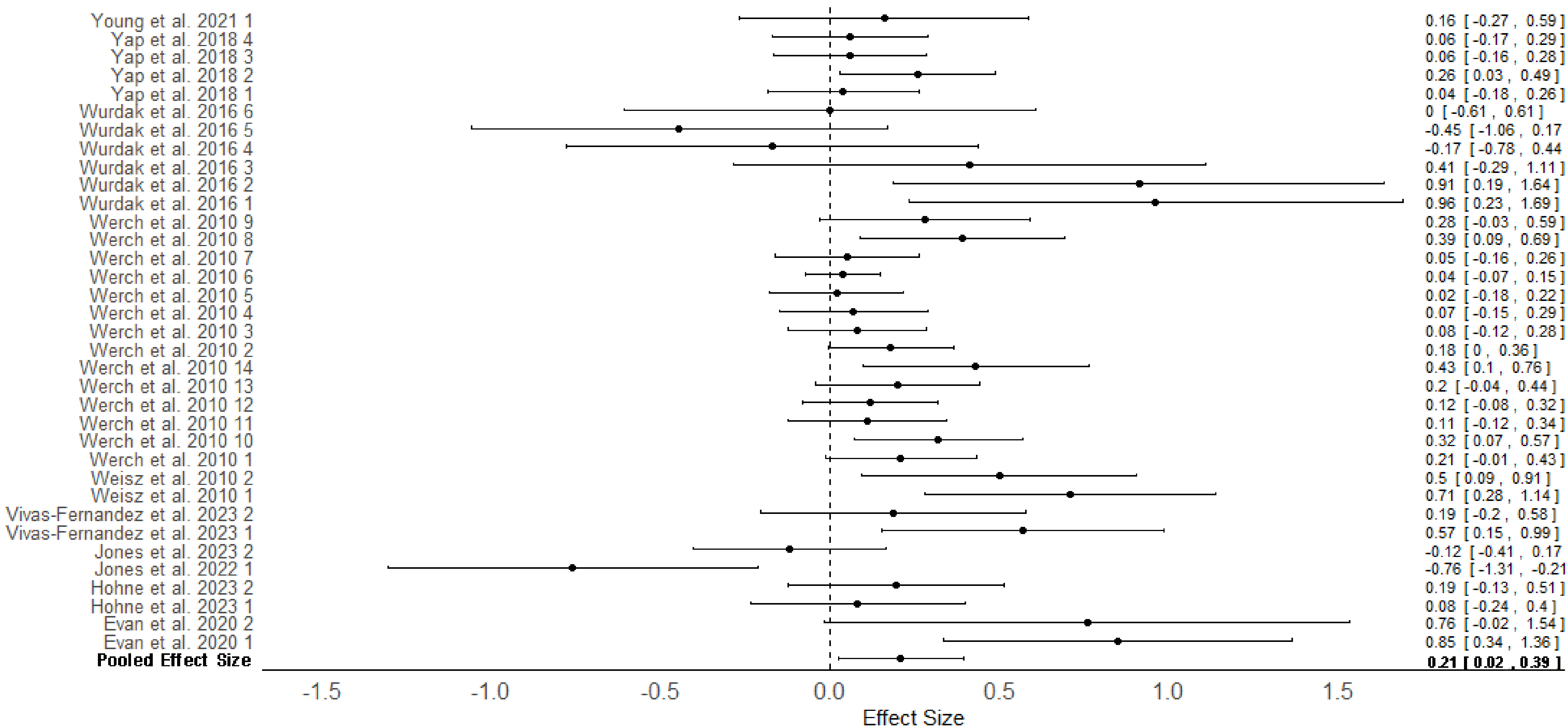
Moderator	Effect Size	Credible Interval	I^2
Type of personalisation			
Treatment matching	0.01	-0.84 to 0.20	63.6%
Individually tailored	0.32*	0.06 to 0.60	46.6%
Mental health Outcome Measure			
Anxiety	0.00	-0.41 to 0.38	83.4%
Depression	0.01	-0.26 to 0.28	0%
Dependent stressors	-0.06	-0.72 to 0.64	N/A
Substance use	0.19	-0.35 to 0.77	38.4%
Trauma	0.14	-0.36 to 0.66	N/A
Internalising & Externalising problems	0.56*	0.00 to 1.18	12.7%
Treatment duration			
Brief	0.18	-0.21 to 0.57	38.4%
Standard	0.42	-0.50 to 0.99	66.4%
Long	0.07	-0.77 to 0.53	67.6%
Treatment delivery method			

Face to face	0.21	-0.14 to 0.58	60.2%
Online/telehealth	0.23	-0.86 to 0.79	30.1%
Hybrid (f2f + online/telehealth)	0.18	-0.77 to 0.81	54.2%
Treatment format			
Individual	0.28	-0.94 to 0.79	50%
Group	0.36	-0.44 to 1.16	44%
Hybrid (group + individual)	-0.06	-1.38 to 0.51	62.8%
Parental involvement			
Adolescent only	0.30*	0.07 to 0.54	50.9%
Parent only	0.09	-0.99 to 0.56	0%
Adolescent & parent	-0.19	-1.20 to 0.21	72%
Method of personalisation			
Component level	0.28*	0.08 to 0.49	50.1%
Intensity level	0.13	-0.96 to 0.65	0%
Package level	-0.19	-1.17 to 0.23	72%
Preventative intervention			
Preventative intervention	0.10	-0.77 to0.31	46.6%
Not preventative intervention	0.32*	0.01 to 0.65	59.5%

Note. *Denotes statistically significant effect sizes. Component level: Participants are matched to specific treatment modules or components. Intensity level: Participants are matched to specific treatment intensities. Package level: Participants matched to specific treatment packages.

Moderation analysis using Risk of Bias as a variable found that studies rated as having low risk of bias had a mean effect size of $d = 0.27$, 95%CrI [-0.03, 0.59], $I^2 = 37.8\%$. Although this was a larger effect size than the primary meta-analysis, it was not statistically significant. Similarly, studies rated as having some concerns yielded a non-significant but smaller effect size of $d = 0.15$, 95%CrI [-0.62, 0.35], $I^2 = 62.2\%$.

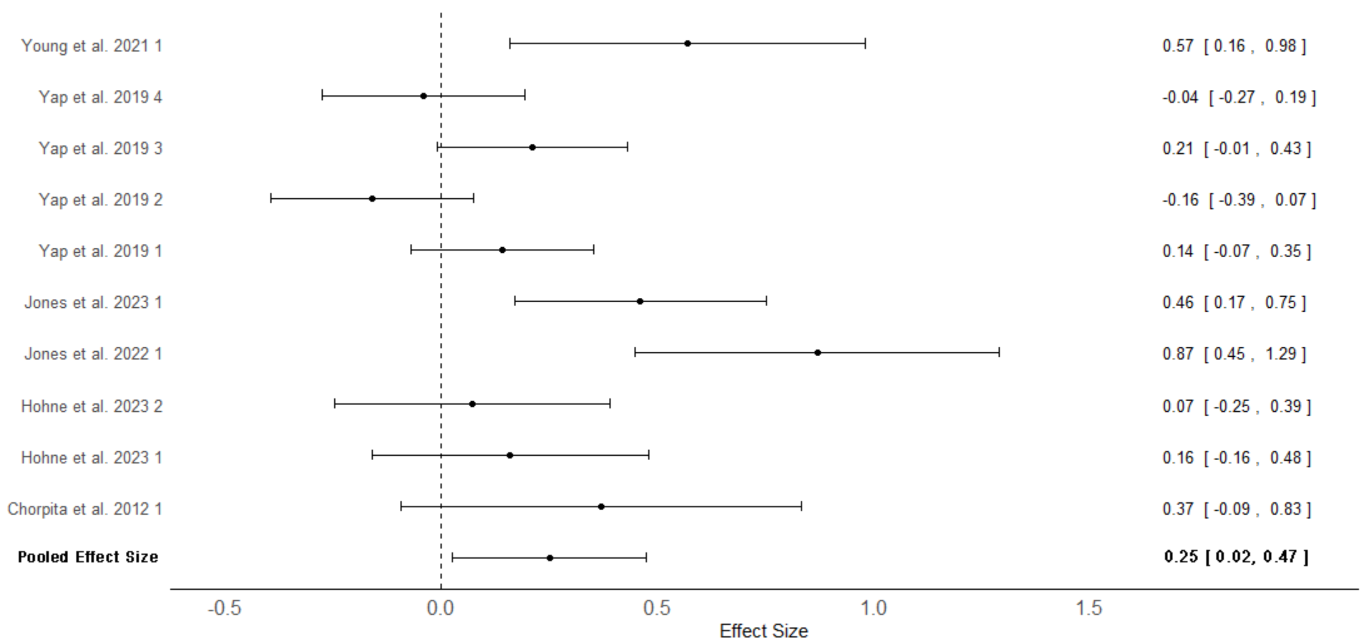
Figure 2. Multilevel Random Effects Meta-Analysis: Outcomes for personalized Intervention versus standardized Interventions in Adolescents.



Note. Numbers next to study authors refers to the effect size number in the study. Some studies reported several effect sizes for differing measures and these were given a number starting from 1.

Six studies ($N = 950$) provided sufficient data to be included in a meta-analysis comparing treatment outcomes for personalized versus standardized interventions at follow-up assessment. The mean effect size was Cohens $d = 0.25$, 95%CrI [0.02, 0.47], $I^2 = 71.2\%$, indicating that personalized interventions were associated with statistically significant superior treatment outcomes compared to standardized interventions at follow-up. Moderation analysis was also conducted however, none of the variables were found to explain potential sources of heterogeneity.

Figure 3. Multilevel Random Effects Meta-Analysis Forest Plot: Follow up Outcomes for personalized versus standardized Interventions in Adolescents.



Note. Numbers next to study authors refers to the effect size number in the study. Some studies reported several effect sizes for differing measures and these were given a number starting from 1.

Publication Bias

Egger's Regression test showed a non-significant *p*-value (p = 0.17 for primary meta-analysis and p = 0.15 for meta-analysis of follow up effects) suggesting the absence of publication bias. This was supported by the Funnel Plot test which showed very minimal funnel plot asymmetry in both plots (Supplementary D). Finally, Trim and Fill method found L_o = 1.45 for the primary meta-analysis and L_0 = 0.11 for the meta-analysis of follow up effects which are both smaller than the recommended cutoff of 2 for a meta-analysis with a population effect size of approximately 0.20 and less than 15 studies, suggesting that there is no evidence of publication bias (Fernandez-Castilla et al., 2021).

Sensitivity Analysis

Sensitivity analysis was conducted by running several variations of the bayesian multilevel meta-analysis using differing priors for means. The differing priors included informative priors: $\mu \sim N(0.22, 0.20)$; $\mu \sim N(0.22, 0.30)$; and $\mu \sim N(0.22, 0.40)$, weakly informative priors: $\mu \sim N(0, 0.12)$; $\mu \sim N(0, 0.50)$, and the non-informative prior $\mu \sim N(0, 1)$. Results of the sensitivity analysis are presented in Supplementary E. The group level and population effects showed minimal change across differing priors suggesting the results reported are relatively robust. However, the 95%CI for the intercept of the weakly informative and non informative priors included zero, whilst the majority of the informative priors did not. These findings that different mean priors led to different interpretations of the model suggest that the results may not be stable. However, the similarity of the estimates across models somewhat decreases this concern (Reis et al., 2023). Overall, sensitivity analysis revealed that the results of the meta-analysis are slightly dependent on prior selection.

Discussion

This systematic review and meta-analysis aimed to explore the efficacy of personalized psychological interventions compared to standardized non-personalized interventions for adolescents. The results indicated that adolescents who received personalized psychological intervention have superior treatment outcomes across the full range of specific outcomes examined compared to adolescents who received standardized non-personalized interventions. The effect size for personalized interventions versus standardized interventions was Cohen's d = 0.21, which is considered a small effect size (Cohen, 1988). This effect size was similar to the effect size of Cohen's d = 0.22 found in adults (Nye et a., 2023) suggesting that personalized interventions may have similar superiority compared to standardized treatments in adolescent and adult populations. More specifically, personalized interventions were found to be associated with superior treatment outcomes compared to standardized interventions in measures of internalizing and externalizing problems with a medium effect size (d = 0.56).

Similar to findings in an adult population, individually tailored approaches to personalisation were associated with superior outcomes compared to standardized interventions (d = 0.32). However, in contrast to adults, treatment-matching approaches were not associated with superior outcomes compared to standardized interventions in adolescents. A possible explanation may be that several studies that used a treatment-matching approach only found superior treatment outcomes favoring personalized intervention at follow-up but not post-intervention (Young et al., 2021; Jones et al., 2022; Jones et al., 2023). Although these studies reported findings from the same sample of adolescents it indicates the possibility that the benefits of personalized interventions may take time to manifest and hints at the longer term positive effects of personalized intervention.

In regards to how personalisation was achieved, component level personalisation (matching to specific treatment modules or components) was associated with superior treatment outcomes compared to standardized interventions (*d* = 0.23). However, intensity level and package level personalisation methods were not associated with improved outcomes compared to standardized interventions. In adults, component level personalisation was found to be a particularly effective method of personalisation (*d* = 0.37) compared to other personalisation methods (Nye et al., 2023) and the findings from the current meta-analysis suggest similar findings in adolescents. These findings suggest that rather than targeting personalisation on a larger scale such as selection of which therapy modality or treatment package to use or the intensity of treatment, that personalisation on a smaller scale targeting the components or kernels of an intervention may be more effective at improving treatment outcomes.

Personalized interventions that targeted the adolescent only (compared to parent only or adolescent and parent interventions) were found to be associated with superior treatment outcomes compared to standardized treatments with a small effect size (*d* = 0.30), suggesting that personalisation is most effective when personalisation is focused solely on the adolescent accessing treatment. Furthermore, personalized intervention was associated with superior treatment outcomes compared to standardized interventions when providing intervention for an ongoing mental health issue (as opposed to a preventative intervention) with an effect size of *d* = 0.32. This was larger than the effect size of the primary meta-analysis (*d* = 0.21) and suggests that personalisation is most effective and best used when designing interventions for adolescents experiencing ongoing mental health issues. In contrast, adolescents receiving interventions aimed at primary prevention of mental health issues may see fewer benefits from personalisation.

personalized interventions were also found to be associated with superior treatment outcomes compared to standardized interventions at follow-up (d = 0.25), indicating that improved treatment outcomes of personalized interventions compared are maintained for up to six to eighteen months post intervention. A core goal of psychological intervention is to cultivate improvement in mental health and psychological functioning which is maintained across time. This goal is even more important for adolescents, as such changes may adjust the long-term mental health trajectory of the individual into adulthood. Therefore the current meta-analysis lends strong support for the benefits of personalizing psychological interventions for adolescents.

In terms of methods of personalisation, there was significant variation across studies in how personalisation was implemented. Methods ranged from using adolescent risk factors determined prior to intervention, case conceptualisation, parent questionnaires, drinking motives, and machine learning algorithms. The findings indicated that there is currently no superior method for achieving personalisation with many varying methods currently available. This is supported by findings by Bastiaansen et al. (2020) who provided an individual client's experience sampling methodology data to 12 different psychology research teams and asked for recommended personalized treatment targets. Interestingly, they found significant variation in how teams analyzed the data, the types of statistics used, and the rationale for targeting the same treatment targets indicating that selection of personalized treatment targets is still highly conditional on subjective analytical choices (Bastiaansen et al., 2020).

Future Research

Across included studies, only one study used a statistical data driven model of personalisation (Ahuvia et al., 2023), and only one study achieved personalisation at the intensity level (Hohne et al., 2023). Consequently, it is still unclear if these forms of personalisation could lead to superior treatment outcomes compared to standardized interventions in adolescents. Further investigation of these methods would be beneficial. Data driven statistical and machine learning models of personalisation incorporate experience sampling methodologies, allowing for intensive repetitive assessment of an individual in their everyday natural environment. These methods may be a particularly promising area for further research given their replicability and the possibility of data-driven algorithmic improvement. This method can also readily link personalization to idionomic analysis of processes of change, which is a direction that is receiving increased attention (Hayes, Ciarrochi, Hofmann, Chin, & Sahdra, 2022; Sahdra, Ciarrochi, Klimczak, Krafft, Hayes, & Levin, 2024).

Strengths and Limitations

The strengths of the current review included the pre-registration of the study protocol, the large number of searched databases, risk of bias analysis with reliability checks, and use of citation searches. Another strength was the use of multilevel Bayseian meta-analysis using priors based on results from a meta-analysis on the efficacy of personalized interventions compared to standardized interventions in adults. The use of a multi-level meta-analysis allowed for consideration of different outcomes measures nesting within studies and studies nesting within samples due to several studies using the same sample. Finally, sufficient studies were available to conduct a secondary meta-analysis exploring the efficacy of personalized interventions compared to standardized interventions at follow-up assessment to explore if benefits of personalisation are maintained over time.

The current study also had several limitations. First, although the meta-analysis yielded a significant effect size favoring personalized intervention, this finding is somewhat dependent on the priors for means used in the analysis. Consequently, these findings need to be updated as additional research exploring personalisation of adolescent interventions emerges, and priors from the current study could be used in future studies and reviews to expand the current findings. Second, the relatively small number of studies included in the meta-analysis of follow-up effects meant that it was not possible to conduct a more robust moderation analysis to investigate potential sources of heterogeneity. Third, the main findings mixed together a wide variety of specific problem areas and outcomes, which may disguise more specific domain-dependent effects. Finally, the exclusion of grey literature and studies not written in English, and that data extraction was performed by one reviewer should be considered.

Clinical Implications

The results of this meta-analysis indicates that in adolescent populations, personalized interventions are associated with superior treatment outcomes compared to standardized non-personalized interventions. Although the calculated effect size of Cohen's $d = 0.21$ is considered a small effect by conventional standards (Cohen, 1988), given the increasingly large number of adolescents experiencing a mental health issue and accessing treatment (Racine et al., 2021), a significantly large number of adolescents may benefit from improved outcomes of personalized interventions. Indeed, this effect size equates to a number needed to treat of NNT = 8.47, meaning approximately 1 in 8 adolescents would experience improved treatment outcomes if personalized interventions were implemented. This is extremely similar to findings in adult populations (NNT = 8.50; Nye et al., 2023) indicating that personalisation could benefit a large proportion of the global population.

The results of the moderation analysis suggest that using an individually tailored approach may be more effective than treatment matching adolescents to specific treatment packages. Specifically, individually tailoring specific components or modules of treatment to suit the needs of the adolescent receiving treatment appears to be the most appropriate and effective method of personalizing interventions. personalized interventions also appear to be most effective when personalisation is focused on the adolescent receiving treatment for an ongoing mental health issue. Finally, personalisation of adolescent interventions may have long-term benefits given it is likely to be early in the course of these disorders.

Conclusion

personalized psychological interventions for adolescents are associated with superior treatment outcomes compared to standardized treatments. These benefits favoring personalized treatments also appear to be maintained at follow-up assessments. These findings indicate that the efficacy of adolescent psychological care could be improved by adopting a personalized approach to intervention.

References

Baker, H. J., Lawrence, P. J., Karalus, J., Creswell, C., & Waite, P. (2021). The Effectiveness of Psychological Therapies for Anxiety Disorders in Adolescents: A Meta-Analysis. *Clinical Child and Family Psychology Review*, *24*(4), 765–782.

Caspi, A., Houts, R.M., Ambler, A., Danese, A., Elliott, M.L., Hariri, A., Harrington, H., Hogan, S., Poulton, R., Ramrakha, S., Rasmussen, L.J.H., Reuben, A., Richmond-Rakerd, L., Sugden, K., Wertz, J., Williams, B.S., Moffitt, T.E., 2020. Longitudinal Assessment of Mental Health Disorders and Comorbidities Across 4 Decades Among Participants in the Dunedin Birth Cohort Study. JAMA Network Open 3, e203221.. https://doi.org/10.1001/jamanetworkopen.2020.3221

Ciarrochi, J., Sahdra, B., Hayes, S. C., Hofmann, S. G., Sanford, B., Stanton, C., Yap, K., Fraser, M. I., Gates, K., & Gloster, A. T. (n.d.). *A personalized-approach to identifying important determinants of well-being*.

Cheung M. W. (2014). Modeling dependent effect sizes with three-level meta-analyzes: a structural equation modeling approach. *Psychological methods*, *19*(2), 211–229. https://doi.org/10.1037/a0032968

Chorpita, B. F., Weisz, J. R., Daleiden, E. L., Schoenwald, S. K., Palinkas, L. A., Miranda, J., Higa-McMillan, C. K., Nakamura, B. J., Austin, A. A., Borntrager, C. F., Ward, A., Wells, K. C., Gibbons, R. D., & Research Network on Youth Mental Health (2013). Long-term outcomes for the Child STEPs randomized effectiveness trial: a comparison of modular and standard treatment designs with usual care. *Journal of consulting and clinical psychology*, *81*(6), 999–1009. https://doi.org/10.1037/a0034200

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates, Publishers.

Cohen, Z.D., Delgadillo, J., DeRubeis, R.J. (2021). Personalized treatment approaches. In M.Barkham, W. Lutz, L.G. Castonguay (Eds.), Bergin and Garfield's handbook of psychotherapy and behavior change, 7th ed. (pp. 667–700). Wiley.

Cuijpers, P., Karyotaki, E., Ciharova, M., Miguel, C., Noma, H., Stikkelbroek, Y., Weisz, J. R., & Furukawa, T. A. (2023). The effects of psychological treatments of depression in children and adolescents on response, reliable change, and deterioration: a systematic review and meta-analysis. *European child & adolescent psychiatry*, *32*(1), 177–192. https://doi.org/10.1007/s00787-021-01884-6

Evans, S. W., Owens, J. S., & Bunford, N. (2014). Evidence-based psychosocial treatments for children and adolescents with attention-deficit/hyperactivity disorder. *Journal of clinical child and adolescent psychology : the official journal for the Society of Clinical Child and Adolescent Psychology, American Psychological Association, Division 53*, *43*(4), 527–551. https://doi.org/10.1080/15374416.2013.850700

Fang, S., & Ding, D. (2020). A meta-analysis of the efficacy of acceptance and commitment therapy for children. *Journal of Contextual Behavioral Science*, *15*, 225–234.

Fernández-Castilla, B., Declercq, L., Jamshidi, L., Beretvas, S. N., Onghena, P., & Van Den Noortgate, W.. (2021). Detecting Selection Bias in Meta-analyzes with Multiple Outcomes: A Simulation Study. *The Journal of Experimental Education*, *89*(1), 125–144. https://doi.org/10.1080/00220973.2019.1582470

Freeman, J., Garcia, A., Frank, H., Benito, K., Conelea, C., Walther, M., & Edmunds, J. (2014). Evidence base update for psychosocial treatments for pediatric obsessive-compulsive disorder. *Journal of clinical child and adolescent psychology : the official journal for the Society of Clinical Child and Adolescent Psychology, American Psychological Association, Division 53*, *43*(1), 7–26. https://doi.org/10.1080/15374416.2013.804386

Goodman, A., Joyce, R., & Smith, J. P. (2011). The long shadow cast by childhood physical and mental problems on adult life. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(15), 6032–6037. https://doi.org/10.1073/pnas.1016970108

Harrer, M., Cuijpers, P., Furukawa, T. A., & Ebert, D. D. (2021). *Doing meta-analysis with R: a hands-on guide*. Chapman and Hall/CRC.

Hayes, S. C., Ciarrochi, J., Hofmann, S. G., Chin, F., & Sahdra, B. (2022). Evolving an idionomic approach to processes of change: Towards a unified personalized science of human improvement. *Behaviour Research and Therapy, 156,* 104155. Doi: 10.1016/j.brat.2022.104155

Higa-McMillan, C. K., Francis, S. E., Rith-Najarian, L., & Chorpita, B. F. (2016). Evidence Base Update: 50 Years of Research on Treatment for Child and Adolescent Anxiety. *Journal of clinical child and adolescent psychology : the official journal for the Society of Clinical Child and Adolescent Psychology, American Psychological Association, Division 53*, *45*(2), 91–113. https://doi.org/10.1080/15374416.2015.1046177

Higgins, J. P., Thompson, S. G., & Spiegelhalter, D. J. (2009). A re-evaluation of random-effects meta-analysis. *Journal of the Royal Statistical Society. Series A, (Statistics in Society)*, *172*(1), 137–159. https://doi.org/10.1111/j.1467-985X.2008.00552.x

Höhne, E., Böge, K., Karnouk, C. *et al.* Culturally sensitive stepped care for adolescent refugees: efficacy and cost–utility of a multicentric randomized controlled trial. *Eur Child Adolesc Psychiatry* (2023). https://doi.org/10.1007/s00787-023-02179-8

Jones, P. J., Mair, P., Kuppens, S., & Weisz, J. R. (2019). An Upper Limit to Youth Psychotherapy Benefit? A Meta-Analytic Copula Approach to Psychotherapy Outcomes. *Clinical Psychological Science*, 7(6), 1434–1449. https://doi.org/10.1177/2167702619858424

Kaiser, T., Volkmann, C., Volkmann, A., Karyotaki, E., Cuijpers, P., Brakemeier, E.-L., 2022. Heterogeneity of treatment effects in trials on psychotherapy of depression.. *Clinical Psychology: Science and Practice* 29, 294–303.. https://doi.org/10.1037/cps0000079

Kaminski, J. W., & Claussen, A. H. (2017). Evidence Base Update for Psychosocial Treatments for Disruptive Behaviors in Children. *Journal of clinical child and adolescent psychology : the official journal for the Society of Clinical Child and Adolescent Psychology, American Psychological Association, Division 53*, *46*(4), 477–499. https://doi.org/10.1080/15374416.2017.1310044

Kieling, C., Baker-Henningham, H., Belfer, M., Conti, G., Ertem, I., Omigbodun, O., Rohde, L. A., Srinath, S., Ulkuer, N., & Rahman, A. (2011). Child and adolescent mental health worldwide: evidence for action. *Lancet (London, England)*, *378*(9801), 1515–1525. https://doi.org/10.1016/S0140-6736(11)60827-1

McHugh M. L. (2012). Interrater reliability: the kappa statistic. *Biochemia medica*, *22*(3), 276–282.

Methley, A.M., Campbell, S., Chew-Graham, C. *et al.* PICO, PICOS and SPIDER: a comparison study of specificity and sensitivity in three search tools for qualitative systematic reviews. *BMC Health Serv Res* 14, 579 (2014). https://doi.org/10.1186/s12913-014-0579-0

Morris, W. K., Vesk, P. A., McCarthy, M. A., Bunyavejchewin, S., & Baker, P. J. (2015). The neglected tool in the Bayesian ecologist's shed: a case study testing informative priors' effect on model accuracy. *Ecology and evolution*, *5*(1), 102–108. https://doi.org/10.1002/ece3.1346

Ng, M. Y., & Weisz, J. R. (2016). Annual Research Review: Building a science of personalized intervention for youth mental health. *Journal of child psychology and psychiatry, and allied disciplines*, *57*(3), 216–236. https://doi.org/10.1111/jcpp.12470

Nye, A., Delgadillo, J., & Barkham, M. (2023). Efficacy of personalized psychological interventions: A systematic review and meta-analysis. *Journal of consulting and clinical psychology*, *91*(7), 389–397. https://doi.org/10.1037/ccp0000820

Oud, M., de Winter, L., Vermeulen-Smit, E., Bodden, D., Nauta, M., Stone, L., van den Heuvel, M., Taher, R. A., de Graaf, I., Kendall, T., Engels, R., & Stikkelbroek, Y. (2019). Effectiveness of CBT for children and adolescents with depression: A systematic review and meta-regression analysis. *European psychiatry : the journal of the Association of European Psychiatrists*, *57*, 33–45. https://doi.org/10.1016/j.eurpsy.2018.12.008

Pettitt, R. M., Brown, E. A., Delashmitt, J. C., & Pizzo, M. N. (2022). The Management of Anxiety and Depression in Pediatrics. *Cureus*, *14*(10), e30231. https://doi.org/10.7759/cureus.30231

Racine, N., McArthur, B. A., Cooke, J. E., Eirich, R., Zhu, J., & Madigan, S. (2021). Global Prevalence of Depressive and Anxiety Symptoms in Children and Adolescents During

COVID-19. *JAMA Pediatrics, 175*(11), 1142. https://doi.org/10.1001/jamapediatrics.2021.2482

Reis, D. J., Kaizer, A. M., Kinney, A. R., Bahraini, N. H., Holliday, R., Forster, J. E., & Brenner, L. A. (2023). A practical guide to random-effects Bayesian meta-analyzes with application to the psychological trauma and suicide literature. *Psychological trauma : theory, research, practice and policy*, *15*(1), 121–130. https://doi.org/10.1037/tra0001316

Sahdra, B.K., Ciarrochi, J., Fraser, M.I. *et al.* The Compassion Balance: Understanding the Interrelation of Self- and Other-Compassion for Optimal Well-being. *Mindfulness* 14, 1997–2013 (2023). https://doi.org/10.1007/s12671-023-02187-4

Silva, S.A., Silva, S.U., Ronca, D.B., Gonçalves, V.S.S., Dutra, E.S., Carvalho, K.M.B., 2020. Common mental disorders prevalence in adolescents: A systematic review and meta-analyzes. PLOS ONE 15, e0232007.. https://doi.org/10.1371/journal.pone.0232007

Venturo-Conerly, K. E., Reynolds, R., Clark, M., Fitzpatrick, O. M., & Weisz, J. R. (2023). Personalizing youth psychotherapy: A scoping review of decision-making in modular treatments. *Clinical Psychology: Science and Practice*, *30*(1), 45–62.

Weersing, V. R., Jeffreys, M., Do, M. T., Schwartz, K. T., & Bolano, C. (2017). Evidence Base Update of Psychosocial Treatments for Child and Adolescent Depression. *Journal of clinical child and adolescent psychology : the official journal for the Society of Clinical Child and Adolescent Psychology, American Psychological Association, Division 53*, *46*(1), 11–43. https://doi.org/10.1080/15374416.2016.1220310

Weisz, J. R., Kuppens, S., Ng, M. Y., Eckshtain, D., Ugueto, A. M., Vaughn-Coaxum, R., Jensen-Doss, A., Hawley, K. M., Krumholz Marchette, L. S., Chu, B. C., Weersing, V. R., & Fordwood, S. R. (2017). What five decades of research tells us about the effects of youth psychological therapy: A multilevel meta-analysis and implications for science and practice. *The American psychologist*, *72*(2), 79–117. https://doi.org/10.1037/a0040360

Weisz, J. R., Kuppens, S., Ng, M. Y., Vaughn-Coaxum, R. A., Ugueto, A. M., Eckshtain, D., & Corteselli, K. A. (2019). Are Psychotherapies for Young People Growing Stronger? Tracking Trends Over Time for Youth Anxiety, Depression, Attention-Deficit/Hyperactivity Disorder, and Conduct Problems. *Perspectives on psychological science : a journal of the Association for Psychological Science*, *14*(2), 216–237. https://doi.org/10.1177/1745691618805436

Weisz, J. R., Chorpita, B. F., Palinkas, L. A., Schoenwald, S. K., Miranda, J., Bearman, S. K., Daleiden, E. L., Ugueto, A. M., Ho, A., Martin, J., Gray, J., Alleyne, A., Langer, D. A., Southam-Gerow, M. A., Gibbons, R. D., & Research Network on Youth Mental Health (2012). Testing standard and modular designs for psychotherapy treating depression, anxiety, and conduct problems in youth: a randomized effectiveness trial. *Archives of general psychiatry*, *69*(3), 274–282. https://doi.org/10.1001/archgenpsychiatry.2011.147

Weisz, J. R., Sandler, I. N., Durlak, J. A., & Anton, B. S. (2005). Promoting and Protecting Youth Mental Health Through Evidence-Based Prevention and Treatment. *American Psychologist, 60*(6), 628–648. https://doi.org/10.1037/0003-066X.60.6.628

Williams, Donald R, Philippe Rast, and Paul-Christian Bürkner. 2018. "Bayesian Meta-Analysis with Weakly Informative Prior Distributions." https://psyarxiv.com/7tbrm/; PsyArXiv.

Young, J. F., Jones, J. D., Gallop, R., Benas, J. S., Schueler, C. M., Garber, J., & Hankin, B. L. (2021). Personalized Depression Prevention: A Randomized Controlled Trial to Optimize Effects Through Risk-Informed Personalization. *Journal of the American Academy of*

Child and Adolescent Psychiatry, *60*(9), 1116–1126.e1.

https://doi.org/10.1016/j.jaac.2020.11.004

Supplementary Materials

Supplementary Materials A

Search Terms

Personali?ed OR individuali?ed OR tailored OR “treatment match*” OR “treatment selection” OR stratif*

AND

Psychotherap* OR intervention* OR therap* OR treatment

AND

adolescen* OR youth OR teen* OR “school student*”

AND

“Mental health” OR "mental disorder" OR depress* OR anxiety OR stress OR trauma OR “eating disorder” OR OCD OR “attention deficit” OR “personality disorder” OR substance

AND

RCT OR randomi?ed

Supplementary Materials B

Characteristic of Included Studies

Study	Country	Setting/delivered format	Participants	Mental Health Issue	Intervention & Type of personalisation	Primary Outcome Measure	Secondary Outcome Measures	Follow up duration
Wurdak et al. (2016)	Germany	Hospital F2f/online hybrid Individual	N=81, Mean age = 15.6 years, SD = 1.0, 42% female	Alcohol use (adolescents hospitalised due to alcohol intoxication)	HaLT intervention + motive-tailored exercises based on evaluated treatment programs or psychological theories (eg., dealing with stress, interpersonal skills, etc.) HaLT intervention + general exercises. Treatment Matching (drinking motives)	Alcohol consumption (adapted from the ESPAD)	N/A	N/A

Hohne et al. (2023)	Germany	Outpatient /Community sample F2f/online hybrid Group/individual hybrid	N=158, Mean age = 18.6 years, SD = 1.58, 16% female. Refugees or asylum seekers.	Depression/Trauma	Level 1- Watchful waiting (PHQ score 5-9) Level 2 – Smartphone app "Balsam" (PHQ score 10-14) Level 3 – Group intervention "START adapt" (PHQ score 15-19) Level 4 – Psychotherapy (PHQ score 20-17) TAU – Psychological support, medication, medical support. Treatment Matching (Based on symptom severity)	Primary Health Questionnaire (PHQ-9)	Child and Adolescent Trauma Screen (CATS)	
Werch et al. (2010)	USA	School health promotion project F2f Individual	N=416, Mean age = 15.8years , SD = 0.77, female 63.5%	Substance use (alcohol, cigarette, marijuana) (preventative)	Brief Image-Based Intervention+ Tailored in person communication involving screening survey, consultation, goal plan). UC – commercially available health promotion materials Individually Tailored	Health and Personal Development Survey, 17 item alcohol and drug problems (Costa et al., 1999).		N/A

Yap et al. (2018)	Australia	Secondary schools/community Online/web based Individual	N = 332 adolescents (359 parents), Mean age = 13.7 years, 44.5% female (child)	Depression and anxiety	Partners in Parenting Intervention (PiP) – web-based parenting program with individually tailored feedback reports. UC – Educational Factsheets Individually Tailored	Parenting to Reduce Adolescent Depression and Anxiety Scale (PRADAS)	Short Mood and Feelings Questionnaire (SMFQ), Spences Children's Anxiety Scale (SCAS)	N/A
Yap et al. (2019)	Australia	Secondary schools/community Online/web based Individual	N = 332 adolescents (359 parents), Mean age = 13.7 years, 44.5% female (child)	Depression and anxiety	Partners in Parenting Intervention (PiP) – web-based parenting program with individually tailored feedback reports. UC – Educational Factsheets Individually Tailored	Parenting to Reduce Adolescent Depression and Anxiety Scale (PRADAS)	Short Mood and Feelings Questionnaire (SMFQ), Spences Children's Anxiety Scale (SCAS)	12-month f/u of Yap et al. (2018)

Vivas-Fernadez et al. (2023)	USA	Community Telehealth Group	N=208, Mean age = 13.71 (SD = 1.41), Female 48.5%	Emotional Problems (preventative)	PROCARE Intervention vs PROCARE+ (PROCARE INTERVENTION + additional models tailored according to adolescent risk factor determined pre-intervention) Treatment Matching (based on risk)	Strength and Difficulties Questionnaire (SDQ),10-Item Connor-Davidson Resilience Scale (CD-RISC-10, KIDSCREEN-10 Index	Difficulties in Emotion Regulation Scale (DERS), Willingness and Action Measure for Children and Adolescents (WAM-C/A), Revised Child Anxiety and Depression Scale (RCADS-30)	
Jones et al. (2023)	USA	Community F2f Individual/ Group hybrid	N = 204, Mean age = 14.26 (SD = 1.65), 56.4% female	Depression (preventative)	Coping with Stress (CWS) Interpersonal Psychotherapy -Adolescent Skills Training (IPT-AST) Treatment Matching (Based on risk)	Adolescent Life Events Questionnaire (ALEQ)	N/A	18 months

Jones et al. (2022)	USA	Community F2f Individual/ Group hybrid	N = 98, Mean age = 13.93 (SD = 1.67), Female 59%	Depression (preventative)	Coping with Stress (CWS) Interpersonal Psychotherapy -Adolescent Skills Training (IPT-AST) Treatment Matching (Based on risk)	Multidimensional Anxiety Scale for Children (MASC), Schedule for Affective Disorders and Schizophrenia for School-Age Children – Present and Lifetime Version (KSADS-PL)	N/A	18 months
Young et al. (2021)	USA	Community F2f Individual/ Group hybrid	N = 204, Mean age = 14.26 (SD = 1.65), 56.4% female	Depression (preventative)	Coping with Stress (CWS) Interpersonal Psychotherapy -Adolescent Skills Training (IPT-AST) Treatment Matching (Based on risk)	Schedule for Affective Disorders and Schizophrenia for School-Age Children – Present and Lifetime Version (KSADS-PL), Children's Depression Inventory (CDI)	N/A	18 months

Ahuvia et al. (2023)	USA	Community, Single Session Intervention (SSI) F2f Individual	N = 996 overall (but only 7 matched and 1 mismatched after algorithm prediction)	Depression	Project Personality (PP) Action Bring Change (ABC) Project Treatment Matching (Based on response to treatment prediction algorithm)	Childrens Depression Inventory 2nd Edition Short Form (CDI-2-SF)	N/A	N/A
Weisz et al. (2012)	USA	Community treatment F2f Individual	N=174, Mean age = 10.59 (SD = 1.76) years, range 7 -13 years old, 30% female	Various (depression, anxiety, conduct, etc.)	MATCH, standardized treatment (Coping Cat for anxiety, PASCET for depression, Defiant Children for disruptive behaviour) Individually Tailored	Brief Problem Checklist (BPC), Top Problems Assessment (TPA)	Children's Interview for Psychiatric Syndromes (Child and Parent versions)	N/A

Chorpita et al. (2013)	USA	Community treatment F2f Individual	N=174, Mean age = 10.59 (SD = 1.76), 30% female	Various (depression, anxiety, conduct, etc.)	MATCH, standardized treatment (Coping Cat for anxiety, PASCET for depression, Defiant Children for disruptive behaviour) Individually Tailored	Child Behaviour Checklist (CBCL), Youth Self-Report (YSR), Brief Impairment Scale (BIS), Services Assessment for Children and Adolescents–Brief Parent Version(SACA)	N/A	2 year follow up of Weisz et al. (2012)
Evans et al. (2020)	USA	Outpatient mental health treatment F2f Individual	N=174, Mean age = 10.6years, SD = 1.8, range 7-13 years, 30% female	Severe irritability	MATCH, standardized treatment (Coping Cat for anxiety, PASCET for depression, Defiant Children for disruptive behaviour), Usual Care Individually Tailored	Child Behaviour Checklist (CBCL) or Youth Self Rating (YSR), Brief Problem Checklist (BPC)	ChIPS, BIS, Youth top problems, BPC	N/A

Supplementary Materials C

Primary Outcomes of Included Studies.

Study	Total N	analyzed N	Narrative outcome	Statistical outcome
Wurdak et al. (2016)	81	personalized = 32 Standard = 49	For girls, those who received a motive tailored/individualised intervention reported lower drinking frequency and less binge drinking post intervention than girls who received standard intervention. For boys, there was no difference between the two groups.	personalized vs standardized time x group interaction. For Girls: Frequency of alcohol consumption: F = 7.770, p = 0.009 Frequency of binge drinking: F = 7.005, p = 0.013 Frequency of drunkenness: F = 1.414, p = 0.243 For Boys: Frequency of alcohol consumption: F = 0.310, p = 0.581 Frequency of binge drinking: F = 2.150, p = 0.150 Frequency of drunkenness: F = 0, p = 0.988

Hohne et al. (2023)	158	TM = 79 TAU = 79	No significant differences between treatment matched group and treatment as usual group in both depression and PTSD symptoms.	No significant difference between TM and TAU: F (02,150) = 0.27, p = 0.762 for depression (PHQ). No significant difference between TM and TAU: F (2,127) = 1.48, p = 0.230 for PTSD symptoms (CATS).

Werch et al. (2010)	416	Tailored = 179 UC = 181 Tailored (drug use history) = 55 UC (drug use history) 46	No significant differences between any measures of alcohol, cigarette, or marijuana use between tailored and UC. However, for adolescents with a history of drug use. Significant differences in drug/alcohol use problems favoring tailored interventions. Also showed reduced frequency of alcohol use, and heavy alcohol use in favor of tailored interventions.	**Effect sizes (Cohen's *d*):** Alcohol frequency: 0.21 Alcohol quantity: 0.18 Alcohol heavy use: 0.08 Marijuana frequency: 0.07 Marijuana quantity: 0.02 Marijuana heavy use: 0.04 Substance use problems: 0.05 **Substance use history subgroup.** Alcohol frequency: 0.39 Alcohol quantity: 0.28 Alcohol heavy use: 0.32 Marijuana frequency: 0.11 Marijuana quantity: 0.12 Marijuana heavy use: 0.20 Substance use problems: 0.43

Vivas-Fernadez et al. (2023)	208	personalized = 52 Standard = 54 Control (UTALK) = 47	Comparison between PROCARE (standardized) and PROCARE+ (personalized) found that PROCARE+ was significantly superior in the reduction of level of emotional risk and separation anxiety reported by parents with small effect sizes. Post-hoc comparisons between ACC (standardized) and PROCARE + found that PROCARE+ was associated with significant improvements in most primary outcome measures.	ACC vs PROCARE +: X^2 (2, N = 99) = 7.42, p = 0.02. PROCARE and PROCARE+: X^2 (2, N = 106) = 0.92, *p* = 0.62.
Jones et al. (2023)	98 (original sample 204)	Matched = 50 Unmatched = 48	Matched and mismatched adolescents did not differ on rates of change in dependent stressors during the intervention (i.e., from baseline to post-intervention). However, matched adolescents showed significantly greater reductions in dependent stressors from baseline to 18 months f/u compared to mismatched adolescents.	Matched vs mismatched post intervention t = -.81, *p* =.42. Matched vs mismatch 18month f/u t=3.17, *p* = .002 Cohen's *d* = 0.46 [0.17, 0.74]

Jones et al. (2022)	98 (original sample 204)	Matched = 50 Unmatched = 48	Matched adolescents showed minimal reductions in anxiety symptoms relative to mismatched adolescents at post intervention. From post-intervention to 18-month follow-up matched adolescents showed a decrease in anxiety symptoms whereas mismatched adolescents showed a significant increase in symptoms.	Matched vs mismatched 18month f/u, *d* = 0.87, *p* =.001 Matched vs mismatched post intervention, *d* = -0.76, *p* = .01 (- negative indicates superior outcomes for mismatched youth)
Young et al. (2021)	98 (original sample 204)	Matched = 50 Unmatched = 48	Matched adolescents showed significantly greater decreases in depressive symptoms than mismatched adolescents from postintervention through 18-month follow-up and across the entire 21-month study period. But no significant differences in depressive symptoms at post intervention.	Matched vs mismatched post intervention *d* = 0.16, *p* = 0.41 18-month f/u *d* = 0.57 CI [0.16, 1.02]
Ahuvia et al. (2023)	996	Lucky = 7 Unlucky = 1	Only eight participants had PAI scores above 0.5 SD: seven ‘lucky’ participants and one ‘unlucky’ participant. Consequently, did not have sufficient data to conduct a t-test comparing outcomes by luck among participants with clinically significant PAI scores. Among all participants (including those whose PAI scores were below 0.5 SD), there were not significant differences in actual RTI between ‘lucky’ participants and ‘unlucky’ participants.	Lucky/matched: M=0.66, SD=1.11 Unlucky/mismatched: M= 0.60, SD=1.09 Comparison: t=0.44, p= .656

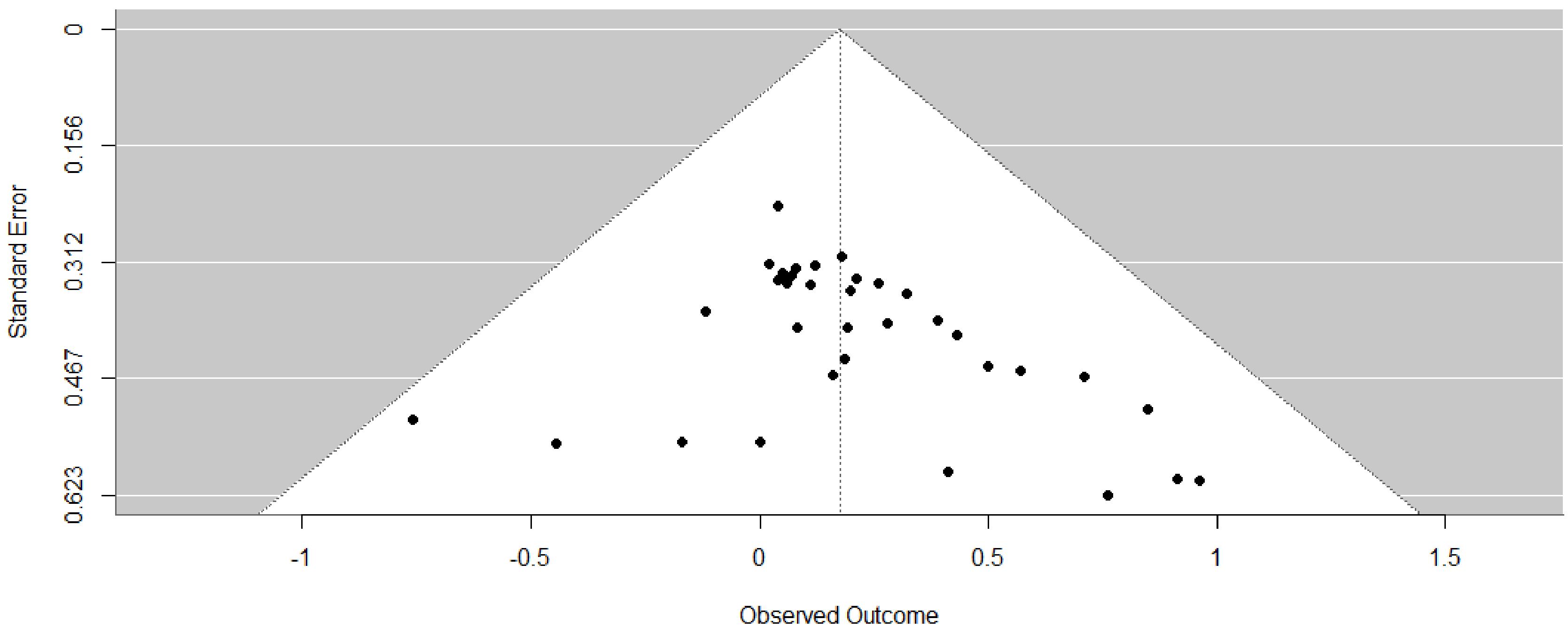
Weisz et al. (2012)	174	Standard Manualised Treatment (SMT) = 69 MATCH (personalized/Modular treatment) = 69 Usual Care (UC)= 64	The findings showed significantly steeper trajectories of improvement in the MATCH intervention than in the SMT intervention on most primary and secondary measures. Also found significant steeper improvement of symptoms in the MATCH intervention than in the UC treatment condition on moist primary and secondary measures.	Effect sizes: MATCH treatment outperformed UC treatment. BPC total: 0.59 *p* =.004 TPA total: 0.54 *p* = .011 MATCH treatment outperformed SMT. BPC total: 0.71 *p* =.001 TPA total: 0.61 *p* = .012
Chorpita et al. (2013)	174	SMT= 69 MATCH= 70 UC= 64	2-year follow up of Weisz et al. (2012). Rate of improvement of internalizing and externalizing symptoms was not significantly different between the modular/personalized (MATCH) intervention and standardized intervention (SMT). However, MATCH was associated with a significant advantage over UC during the 2-year assessment period, whereas the treatments in the SMT group was not.	Effect Sizes: MATCH vs STM (Total overall problems) = 0.37 MATCH vs UC (Total overall problems) = 0.65 MATCH vs UC (Youth report) = 0.45 MATCH vs UC (Caregiver report) = 0.59 MATCH vs STM (Youth report) = 0.29 MATCH vs STM (Caregiver report) = 0.11

Evans et al. (2020)	174 (93 subsample of SIMD)	SMT = 26 MATCH = 26 UC = 24	Among adolescents with SIMD, those in the MATCH intervention showed statistically significant and reliable within-group improvement per all measures and both informants (parent and adolescent). In contrast, UC and SMT both tended to show within-group improvement on caregiver-reported measures but not consistently on all youth-reported measures. MATCH also produced faster rates of improvement relative to UC or SMT, or both. Finally, MATCH and SMT both led to meaningful reductions in functional impairment relative to UC, however, only MATCH predicted significantly fewer diagnoses at post-treatment.	Effect Sizes: MATCH vs SMT BPC total (Caregiver)= 0.85 MATCH vs SMT BPC total (Youth) = 0.76
Yap et al. (2018)	359 (parent child dyad)	PiP = 179 Control = 180	No significant interactions between condition and time on the SMFQ-P, SMFQ-C, and SCAS-P scores. Across both conditions (personalized and standardized), parents reported significantly decreased symptoms of depression and anxiety from baseline to post intervention.	Effect sizes (Cohen’s d): SCAS-P: 0.04 (−0.18 to 0.26) SCAS- C: 0.26 (0.03-0.48) SMFQ-P: 0.06 (−0.16 to 0.28) SMFQ-C: 0.06 (−0.17 to 0.28)

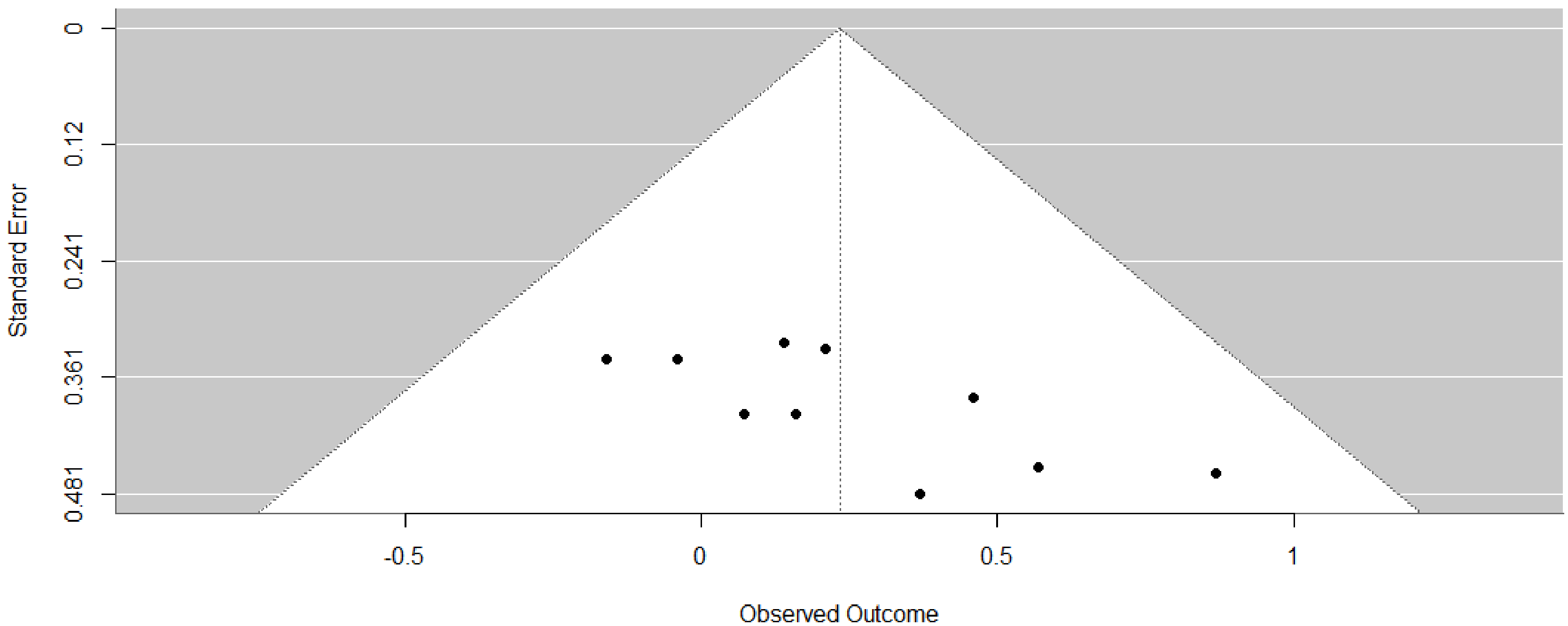
Yap et al. (2019)	359 (parent child dyad)	PiP = 179 Control = 180	No indication that PiP (personalized intervention) significantly reduced adolescent depression and anxiety symptoms as reported by either parents or adolescents, compared to standardized intervention at 12-month follow up. Consistent with findings at postintervention, suggesting that the effect of PiP was not associated with significant reductions in adolescent symptoms compared with a standardized intervention.	Effect sizes (Cohen's d): (nNgative scores indicate greater reduction in scores in personalized intervention group) SCAS-P = −0.14 (−0.37 to 0.08) SCAS-C = 0.16 (−0.07 to 0.39) SMFQ-P = −0.21 (−0.42 to 0.01) SMFQ-C = 0.04 (−0.19 to 0.27)

Supplementary Materials D

Funnel Plot for Primary Meta-Analysis Exploring personalized Interventions versus standardized Interventions.



Funnel Plot for Secondary Meta-Analysis Exploring personalized Interventions versus standardized Interventions at Follow-up.



Supplementary Materials E

Effects sizes estimates, standard errors (SE), and Credible Intervals for primary Bayesian meta-analysis using different means priors.

Priors	Sample (SE)	Sample/Author (SE)	Sample/Author/Measure (SE)	Population Level Effects (SE)	Credible Intervals
μ ~ N(0.22, 0.20)	0.23 (0.13)	0.18 (0.13)	0.06 (0.04)	0.20 (0.10)	0 to 0.41
μ ~ N(0.22, 0.30)	0.24 (0.13)	0.18 (0.13)	0.06 (0.04)	0.20 (0.12)	-0.03 to 0.44
μ ~ N(0.22, 0.40)	0.24 (0.13)	0.18 (0.13)	0.06 (0.04)	0.20 (0.12)	-0.05 to 0.45

μ ~ N(0, 0.12)	0.24 (0.13)	0.19 (0.14)	0.06 (0.04)	0.10 (0.09)	-0.09 to 0.26
μ ~ N(0, 0.50)	0.24 (0.13)	0.18 (0.13)	0.06 (0.04)	0.18 (0.13)	-0.08 to 0.44
μ ~ N(0, 1)	0.24 (0.14)	0.18 (0.14)	0.06 (0.04)	0.19 (0.13)	-0.07 to 0.46