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Dropout rates of in-person psychosocial substance use disorder treatments: a systematic review and meta-analysis

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ABSTRACT

Background and Aims Relapse rates for psychosocial substance use disorder (SUD) treatments are high, and dropout is a robust predictor of relapse. This study aimed to estimate average dropout rates of in-person psychosocial SUD treatments and to assess predictors of dropout. **Design** A comprehensive meta-analysis of dropout rates of studies of in-person psychosocial SUD treatment. Studies included randomized controlled trials (RCTs) and cohort studies. **Setting** Studies conducted anywhere in the world that examined SUD treatment and were published from 1965 to 2016, inclusive. **Participants/cases** One hundred and fifty-one studies, 338 study arms and 299 dropout rates including 26 243 participants. **Measurements** Databases were searched for studies of SUD treatment that included an in-person psychosocial component. Meta-analyses and meta-regressions were conducted to estimate dropout rates and identify predictors of dropout, including participant characteristics, facilitator characteristics and treatment characteristics. Pooled estimates were calculated with random-effects analyses accounting for the hierarchical structure of study arms nested within studies. **Findings** The average dropout rate across all studies and study arms was 30.4% [95% confidence interval (CI) = 27.2–33.8 and 95% prediction interval (PI) = 6.25–74.15], with substantial heterogeneity (I^2 = 93.7%, $P < 0.0001$). Studies including a higher percentage of African Americans and lower-income individuals were associated with higher dropout rates. At intake, more cigarettes/day and a greater percentage of heroin use days were associated with lower dropout rates, whereas heavier cocaine use was associated with higher dropout rates. Dropout rates were highest for studies targeting cocaine, methamphetamines and major stimulants (broadly defined) and lowest for studies targeting alcohol, tobacco and heroin, although there were few studies on methamphetamines, major stimulants and heroin. Programs characterized by more treatment sessions and greater average session length were associated with higher dropout rates. Facilitator characteristics were not significantly associated with dropout. **Conclusions** On average, approximately 30% of participants drop out of in-person psychosocial SUD treatment studies, but there is wide variability. Dropout rates vary with the treated population, the substance being targeted, and the characteristics of the treatment.

Keywords Addiction, attrition, dropout, meta-analysis, retention, substance dependence, substance use disorder, treatment.

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INTRODUCTION

Approximately 250 million people world-wide use addictive substances every year, and of these, nearly 30 million suffer from substance use disorders (SUDs [1]). Only one in six individuals with SUDs enter psychosocial treatment, and psychosocial SUD treatment relapse rates generally range from 40 to 60%, with some relapse rates reaching as high as 86% [2]. Psychosocial treatment can include in-person mental health services with a trained clinician (i.e. counseling, cognitive behavioral therapy or psychotherapy), vocational services and social services. Psychosocial SUD treatment dropout is a widely noted problem in the addiction field, and has long been a robust predictor of relapse [3–8]. Indeed, dropout is frequently used as both a process and an outcome variable in research studies, can indicate

the acceptability/relevance of psychosocial treatments and can signal the possibility of differences in missing data across conditions [9].

For years, dropout has been recognized as a key factor affecting SUD treatment effectiveness [3–8]. Treatment participation and retention are consistently related to beneficial post-discharge outcomes [10–15], whereas participants who drop out of treatment prematurely often produce high front-end costs without benefiting from the full course of intervention. High dropout can therefore reduce both the efficiency and effectiveness of a treatment program [12,16].

Despite the importance of dropout as both a process and outcome measure, no meta-analyses have been conducted to determine the magnitude of dropout in the psychosocial treatment of SUDs. One prior meta-analysis published in 2008 [17] evaluated interventions for cannabis, cocaine, opiate and polysubstance use (n = 34 studies). Although dropout rates were reported for a portion of included studies, dropout itself was not a specific focus of this meta-analysis, and interventions for alcohol and tobacco use, which form the majority of trials for psychosocial SUD treatment, were excluded. Reported dropout rates in the research literature otherwise range from zero [18,19] to 100% [20]. This variance suggests the need for a comprehensive review to provide an average estimate and identification of predictors of this important variable.

To our knowledge, only one study has focused on dropout in psychosocial SUD treatment. A systematic review [21] identified younger age, cognitive deficits, personality pathology, increased treatment length and decreased therapeutic alliance as potential risk factors for dropout. However, the authors noted a dearth of relevant research findings, and called for a meta-analysis to further evaluate dropout in psychosocial SUD treatment.

Previous meta-analyses on dropout in adult psychotherapy excluded SUD treatments [22,23]. Although the reasons for excluding such treatments from meta-analyses are unclear, the mental health field has a history of overlooking substance use [24]. Despite the prevalence of SUDs and the array of clinical contexts in which people with SUDs present for treatment, mental health-care providers often presume that these disorders are best treated in specialized programs. However, psychosocial problems often abate when substance use is stopped or reduced (e.g. [25,26]).

Poor understanding of psychosocial SUD treatment dropout is likely to impede the successful development and evaluation of interventions [27]. Quantifying dropout affects power analyses, the assessment of the feasibility of interventions and the ability to gauge the success of treatment. Furthermore, poor understanding of predictors of dropout impedes attempts to minimize this negative outcome. In the behavioral health field as a whole, and in the SUD treatment field in particular, the focus is shifting to designing, implementing and evaluating individually tailored interventions that suit the distinct, yet shared, needs of various subgroups of clients [28,29]. Current research interests have focused on identifying relationships among participant-, facilitator- and treatment-level variables and investigating how they relate to other outcomes, including dropout [30–34]. Thus, elucidating predictors of dropout will advance tailored interventions designed to reduce dropout, thereby enhancing overall efficacy. The objectives of this meta-analysis, therefore, were to estimate average dropout rates of in-person psychosocial SUD treatments and to test for the effect of potential predictors of this outcome.

METHODS

Literature search and selection

Data extraction was conducted in duplicate by the first author together with one graduate research assistant and one undergraduate research assistant (see Acknowledgements). The first pass of screening was performed in singlet, with a default towards inclusion; any uncertainty was confirmed by a second rater. The three individuals compared independently extracted data for discrepancies and reached consensus through discussion. Studies were reviewed that examined SUD treatment and were published from 1965 to 2016, inclusive. This start date was selected to align with what is considered the advent of the modern mental health era [23]. We searched for specific substances separately ('alcohol', 'barbiturates', 'benzodiazepines', 'cannabis', 'cocaine', 'ecstasy', 'γ-hydroxybutyric acid (GHB)', 'hallucinogen', 'heroin', 'marijuana', '3,4 methylenedioxy methamphetamine (MDMA)', 'methamphetamine', 'morphine', 'nicotine', 'oxycodone' and 'tobacco') and broad classifications, including 'depressants', 'opiates/opioids', 'polysubstance' and 'stimulants' in combination with one of the following words, which were used in every search: 'dropout', 'attrition' and 'retention', and also included the following modifiers: 'addiction', 'behavioral treatment', 'clinical trial', 'substance abuse', 'substance dependence', 'substance use' and 'treatment'. These terms were searched to ensure the compilation of studies investigating treatment modalities for SUD. Two examples would be 'cocaine' AND 'retention' AND 'clinical trial' or 'stimulants' AND 'attrition'.

All articles were first assessed for general eligibility: (1) the study must have examined treatment for substance use in humans over the age of 18 years; (2) treatment must have included a psychosocial component; (3) treatment must have been in-person; and (4) the article had to define and report dropout. All intervention designs were included, including single-arm, uncontrolled studies. Articles that met the general inclusion criteria were then screened

according to the following exclusion criteria: (1) treatment involved only self-help or technology; (2) substance use was a secondary outcome (e.g. studies examining weight status as the primary outcome); (3) treatment involved children or adolescents; (4) studies not available in English; (5) unpublished reports; and (6) studies investigating non-humans. Articles were excluded upon identifying any single exclusion criterion or failure to meet an inclusion criterion.

Selection of the outcome variable and predictor variables

The outcome variable was treatment dropout, operationalized as the proportion of participants who initiated but did not complete treatment.

We organized predictor variables into three categories: (1) participant characteristics; (2) facilitator characteristics; and (3) treatment characteristics. Herein, we use the term predictor to mean a variable that may potentially explain variability in dropout rates. Table 1 outlines predictor variables selected for analysis that were chosen as a complement to and comparison of meta-analyses of dropout in adult psychotherapy [22,23], as well as in accordance with suggestions from a prior systematic review of risk factors of psychosocial SUD treatment dropout [21] and recommendations for systematic reviews of interventions [40]. It is important to note that predictor variables represent aggregates across participants within studies or study arms. For instance, the income variable represents the average income of participants within a study or study arm. Inferences about associations therefore need to be drawn concerning dropout rates as a function of average income, which does not necessarily reflect the propensity for a given individual with a particular income to drop out of a study. It could be, for instance, that there is a structural difference between studies enrolling higher earners than lower earners, rather than a direct function of income on someone's propensity to dropout. For more specific information regarding selected variables, please refer to the data dictionary in the Supporting Information.

Statistical analysis and software

All analyses were conducted using R version 3.5.1. Meta-analyses and meta-regressions were calculated using the metafor package (version 2.0.0) using the rma.mv function. Effect sizes for each dropout rate were calculated using the escalc function with PLO as the measurement option (logit-transformed proportion). Final analyses used random-effects models. Where appropriate, 95% prediction intervals (PI) were also calculated in addition to 95% confidence intervals (CI) because of significant heterogeneity. The only variables coded that we did not analyze directly are 'country' and 'income', because we chose instead to dichotomize country by developing/developed (reported as 'country classification') and to adjust income for inflation (reported as 'adjusted mean annual income'), respectively. Untransformed 'country' and 'income' variables can be found in the Supporting Information. Because the Addiction Severity Index (ASI) was reported inconsistently across studies, it was excluded. Multiple comparisons were not taken into consideration because: (1) the analyses were intended to be descriptive; (2) the analyses use data that are dependent among analyses, and thus the assumptions of typical multiple comparison correction procedures would be violated; and (3) there are disagreements in the literature of whether and how to take multiple comparisons into consideration. We report all analyses with exact *P*-values so that readers can estimate a conservative Bonferroni-type correction by dividing the chosen alpha of 0.05 by the number of comparisons in the family of analyses of the reader's choosing, and comparing the resultant *P*-values to the Bonferroni-corrected alpha. Note that relying on significance thresholds with the *P*-values as reported increases the risk that at least one will be significant by chance (type I error), while using a Bonferroni-type correction increases the risk of excluding true associations (type II error).

Although publication bias is typically investigated in meta-analyses, it was not formally evaluated herein because the dropout rates are ancillary outcomes, meaning that the selective pressure to publish or not as a function of dropout rate is unclear other than a general likelihood that increasing dropout may be associated with lower probability of publication. If this assumption is true, then it means the dropout rates may be conservative (i.e. lower than would be expected if there was no publication bias) but, to the best of our knowledge, no functional form of measuring or correcting for publication bias in meta-analyses of single-proportion data exists.

Data cleaning

A detailed description of data cleaning and data checking procedures can be found in the Supporting Information, particularly in section '2 Data import and cleaning'. Briefly, dropout rates were tested for the logical constraint that the proportion had to be between 0 and 1; uniqueness of identifiers were confirmed; articles with dropout rates that were averaged across multiple study arms were excluded if any of the study arms were excluded (see '2.2 Data inclusion/exclusion rules' in the Supporting Information); and dropout rates were converted to numbers of participants who dropped out to facilitate calculating effect sizes for each study or study arm, as appropriate. The available data were compared for each individual predictor analysis, including determining whether predictor values differed between study arms in which there was only a single dropout reported, or if multiple predictor values occurred within a single study arm (e.g. the use of multiple individual

Table 1 Predictor variables.

Predictor category	*Variable*	*Data note*
Participant	Age	Mean years
	Sex	Proportion male
	Education	Mean years completed
	White	Proportion
	Hispanic/Latino	Proportion
	African American	Proportion
	Other race/ethnicity	Proportion not White, Hispanic/Latino or African American
	Adjusted mean annual income	Mean annual household income in US dollars, adjusted for inflation[a]
	Not married	Proportion not married
	Unemployed	Proportion unemployed
	Not unemployed	Proportion not unemployed[b]
	Frequency of use	Mean percentage of substance use days at intake, reported separately for each substance
	Length of use	Mean length of substance use in years at intake, reported separately for each substance
	Degree of use	Light, moderate, or heavy at intake, reported separately for each substance[c]
	Drinks per day	Mean standard drinks consumed per day at intake
	Cigarettes per day	Mean cigarettes smoked per day at intake
	Treatment-seeking?	No or not indicated, yes, mixed
	Mood disorder	Percentage
	Anxiety disorder	Percentage
	Comorbid substance use dependence/addiction	Percentage
	Personality disorder	Percentage
	Other psychological diagnoses	Percentage
Facilitator		
	Experience	Years of practice if one facilitator, mean years of practice if more than one facilitator
	Degree	Bachelors, Masters, Doctorate, Certificate or mixed (multiple degrees when more than one facilitator)
Treatment		
	Publication year	Year study was published
	Substance being targeted	Alcohol, tobacco, cocaine, opioids, methamphetamine, cannabis, polysubstance, heroin, major stimulants[d]
	Pregnant participants?	No or not indicated, yes
	Manualized treatment?	No or not indicated, yes
	Sessions	Number of treatment sessions
	Session length	Average in minutes
	Treatment window	Period of time over which treatment was provided in weeks
	Setting of trial	Institution, out-patient (hospital/medical school), out-patient (public), university-affiliated clinic, in-patient, mixed
	Pharmacotherapy category[e]	No, placebo, not agonist, agonist
	Treatment approach	Cognitive and/or behavioral, motivational, psychodynamic, 12-Step, integrative, non-specific
	Limited treatment time?	No or not indicated, yes
	Training for fidelity?	No or not indicated, yes
	Treatment format	Group, individual, mixed, not specified, couple therapy
	Efficacy study?	Efficacy, effectiveness
	Codification of dependence	Diagnostic and Statistical Manual (DSM) diagnosis, other
	Country classification	Developed, developing[f]

[a]Adjusted using the CPI Inflation Calculator at https://data.bls.gov/cgi-bin/cpicalc.pl. [b]'Unemployed' and 'not unemployed' are not complements because of differences in reporting among studies. For example, an employment status of 'retired', 'student' or 'disabled' could not be assumed to mean either employed or unemployed. [c]Defined in [35–38]. [d]Despite being part of our original search, no studies targeting depressants, hallucinogens, or γ-hydroxybutyric acid (GHB) fit our criteria. [e]The 'active' pharmacotherapy category was split into 'agonist' and 'not agonist' *post hoc* at the suggestion of a reviewer. [f]According to the World Health Organization; DPAD [39].

substances was reported within a study; see '2.2 Data inclusion/exclusion rules' in the Supporting Information). The final counts of included articles, study arms and dropout rates are depicted in Fig. 1. The included articles and dropout rates for each analysis are reported throughout the text. We reviewed the predictor analysis plots *post hoc* (described below), and saw few data points that appeared to constitute outliers. More extreme values tended to be from smaller studies, and thus are down-weighted in analyses; alternatively, some extreme values were in analyses with few data points, and thus there were insufficient data to conclude that the extreme values were atypical. Because there was no a priori functional form to define outliers, we have included all data herein.

Estimating overall dropout rates

The primary analysis for calculating overall dropout rates was a random-effects meta-analysis, treating each dropout rate as nested within study. In some cases, only one dropout rate was reported for a given study (e.g. only a single eligible study arm) or only pooled dropout rates were reported (see section '3 Estimating overall dropout rates' in the Supporting Information).

Estimating subgroup meta-analyses for categorical predictors

Random-effects meta-analyses were calculated for each categorical predictor variable (see '4.1 Categorical study-level predictors' and '5 Study arm-level predictors: Substances' for use pattern in the Supporting Information). These models used the same inverse-variance, hierarchical approach as the overall model, but included categorical variables for subgroup analyses in univariate analyses, not controlling for other factors. Some studies reported multiple substances used by the participants, even if the substances were not the target of the intervention.

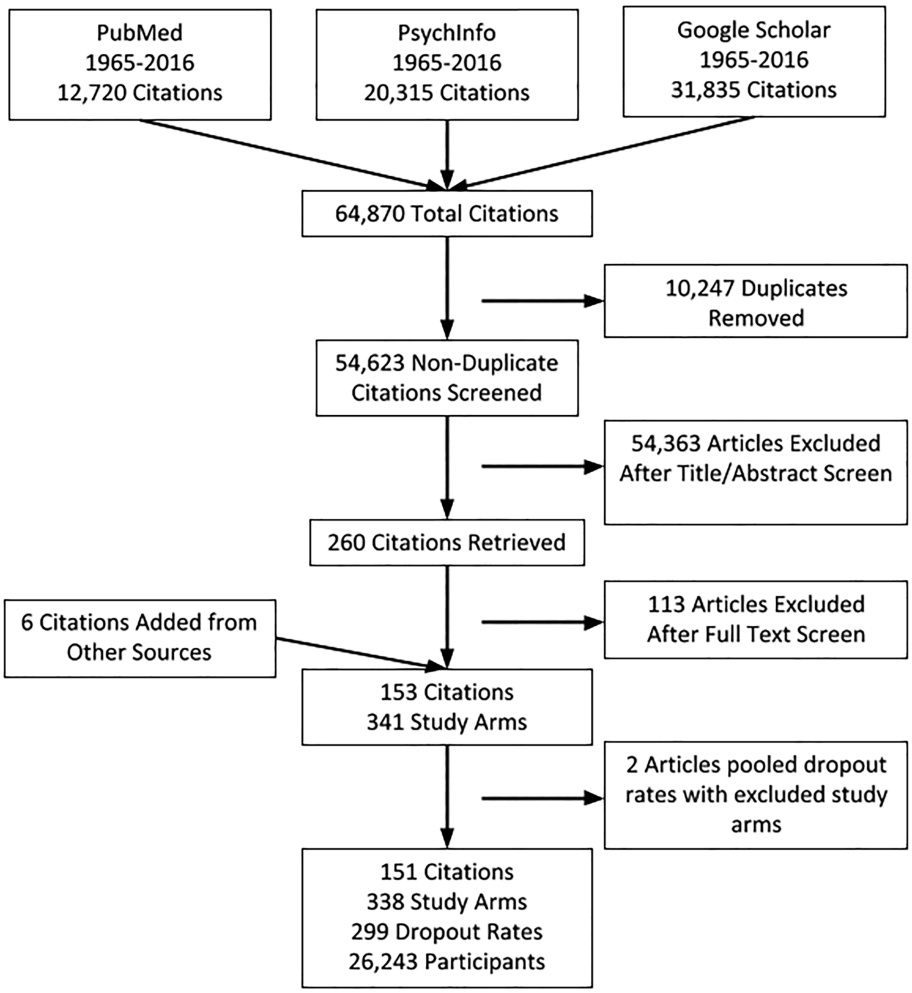

Figure 1 PRISMA diagram for literature screening. The difference between study arms and dropout rates is because some studies include only pooled dropout rates over multiple study arms. The number of included studies and dropout rates varies from analysis to analysis dependent on whether the predictor was reported in a given study. The number of included studies and dropout rates are reported for each analysis elsewhere in the paper.

However, simultaneously modeling all substances used in a single predictor analysis was not possible because of independence issues, namely that the same study arm could have reported participants using more than one substance and would therefore be counted twice in a simultaneous model. We chose to test each reported substance separately, excluding arms with more than one substance in the same class (e.g. multiple different opiates) for the analysis of that substance. The overall tests of predictor variables are reported, with a *P*-value less than 0.05 indicating a global, significant difference among subgroups; pairwise subgroup comparisons are not reported, but individual subgroup 95% CI are reported.

Estimating meta-regressions for continuous predictors

Random-effects meta-regressions were calculated based on the inverse-variance, hierarchical approach for each continuous predictor variable (see '4.2 Continuous study-level predictors', '5 Study arm-level predictors: Substances' and '6 Study arm-level predictors: Diagnoses' in the Supporting Information). Continuous predictors were included as linear terms in univariate analyses, not controlling for other factors. Note that meta-regression predictor terms were often point estimates of characteristics of the study samples, such as the percentage of participants who were male within a study arm. The limitation of simultaneously testing multiple reported substances described above holds for the meta-regressions, and further applies to comorbid diagnoses. The overall tests of predictor variables are reported, with a *P*-value less than 0.05 indicating a significant slope.

Estimating heterogeneity

Each analysis also includes an estimate of total heterogeneity using the methods of Higgins *et al.* [41], and calculated as described in the documentation for the metafor package (see functions: R file in the Supporting Information code). Because of the hierarchical nature of the models, I^2 is presented as the sum of the within- and between-study arm heterogeneity estimates. *P*-values for heterogeneity or residual heterogeneity for predictor analyses are derived from Q-statistics (see Supporting Information results).

Supplementary methods, data, code and results

Additional methods, data, statistical code and results of all analyses, including diagnostic plots, forest plots, and meta-regressions for each predictor variable, can be found in an online repository at https://doi.org/10.5281/zenodo.3237284.

RESULTS

Screening and study characteristics

Figure 1 shows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) diagram. Because some studies reported a single dropout rate pooled across study arms, there were 338 eligible study arms but only 299 dropout rates, including 26 243 participants. In approximately 85% of studies, dropout was reported for each study arm, whereas in the remainder dropout was pooled across study arms.

After screening the articles based on the inclusion/exclusion criteria, the remaining articles described treatments targeting alcohol, tobacco, cocaine, opioid, methamphetamine, cannabis, polysubstance, heroin and major stimulant (broadly defined) use. In some predictor analyses available data were limited, and either no studies, a single study arm, a single study or a single predictor value were available. In the footnotes of the predictor analysis tables, we note which analyses were omitted because data were insufficient to calculate meaningful regressions (e.g. in the case of only a single study being available, the analysis would only report a summary of that study). In some analyses, only a single study or arm was available among a group of predictors, and thus associations could still be calculated. For instance, the 'pregnant participants' variable in Table 6 has only a single dropout rate. Although a legitimate comparison can be calculated, readers should be cautious to evaluate how many dropout rates are available for a given comparison when interpreting the results.

Summary information about the studies are shown for each predictor analysis. For instance, Table 3 shows that the 1st quartile, median and 3rd quartile of study arm average participant age are 34, 39 and 43 years, respectively; and Table 6 includes a summary of how many studies were targeted at addressing each of the nine identified substances: only one study looked at major stimulants (broadly defined) or methamphetamines each, while 65 studied tobacco.

Overall dropout rate

The meta-analytical forest plot of dropout rates is available in Fig. 2. As seen in this figure, dropout rates ranged from 0 to 100%, with an average dropout rate of 30.4% across all studies (95% CI = 27.2−33.8). Given the heterogeneity in outcomes (I^2 = 93.7%, $P < 0.0001$), the 95% PI or the estimate of the interval in which a future study will fall ranged from 6.25 to 74.15%.

Residual heterogeneity in predictor analyses

Because of the significant and substantial heterogeneity in the overall dropout rate analysis, which is to be expected

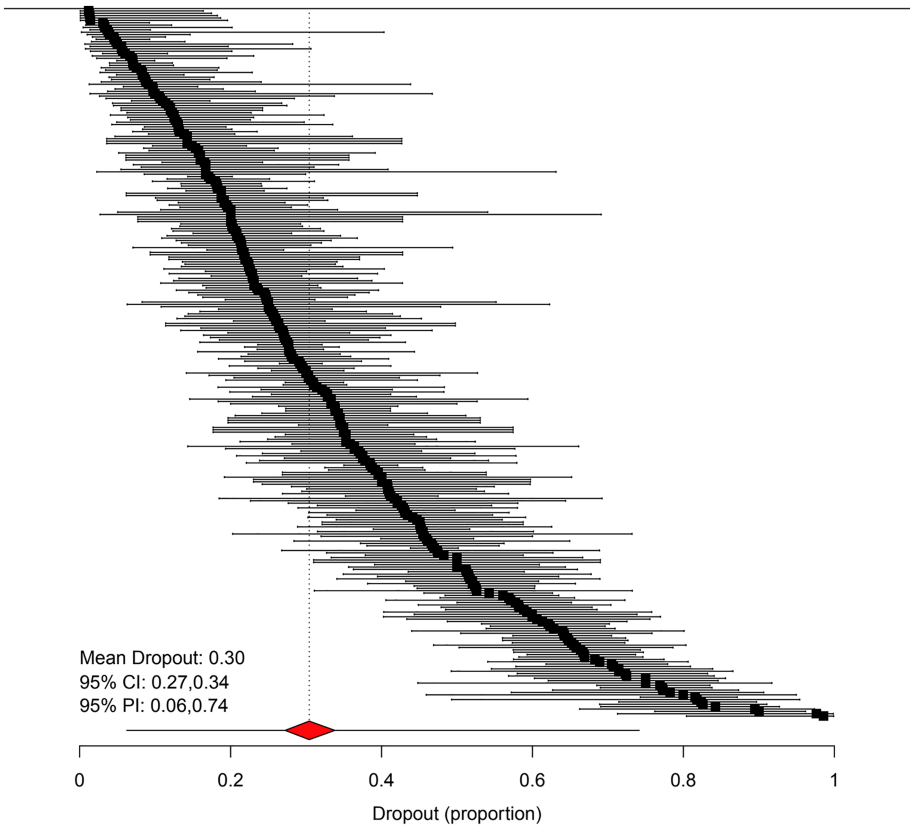

Figure 2 Forest plot of all included dropout rates. Each square and horizontal line represents the proportion and 95% confidence interval for a given study or study arm. The vertical dashed line represents the average dropout rate across studies and the diamond represents the average dropout rate across studies and its 95% confidence interval. The horizontal line on the summary diamond represents the 95% prediction interval [Colour figure can be viewed at wileyonlinelibrary.com]

given the variety of types of studies included, single-predictor analyses were conducted. These were conducted on the full set of dropout rates where possible, or conducted on subsets of reported substances or comorbid diagnoses when independence among study arms was violated, as described in the Methods. Below, the results of the predictor analyses are described. However, for all cases, there was significant residual heterogeneity, even when the predictor explained a statistically significant amount of the variability. The reader is therefore cautioned that important sources of variability among dropout rates are not always identified in our models, and thus the direction and nature of the predictor–dropout relationships may differ in direction or magnitude (even for non-significant predictors) when controlling for other variables or in particular subsets of studies (e.g. stratified by sex).

Predictors: participant characteristics

Tables 2 and 3 display results of predictor analyses of categorical and continuous participant characteristics, respectively. Studies with a greater percentage of African Americans produced higher dropout rates, from 24.5% dropout when the proportion of African Americans was 0.07 in a study (first quartile, Q1) to 37% dropout when the proportion was 0.52 (third quartile, Q3) estimated from 74 studies/142 dropout rates; whereas studies with a greater percentage of individuals of 'other' racial identities produced statistically significant but modestly lower dropout rates, from 33.8% dropout when the proportion of 'other' was 0.0 (Q1) to 31.2% dropout when the proportion was 0.08 (Q3) estimated from 74 studies/142 dropout rates. Studies with participants with a lower income were also associated with higher rates of dropout: using 16 studies with 34 dropout rates, 41% dropout was estimated with an average adjusted group income of $9726 (Q1), while 33.5% dropout was estimated when the income was $26 670 (Q3). With regard to SUD-specific variables, lower rates of dropout were observed for studies that included participants who reported a greater number of cigarettes smoked per day at intake (27.4% dropout at Q1 of 19 cigarettes per day to 21.4% dropout at Q3 of 26 cigarettes per day; estimated from 54 studies/106 dropout rates) and a greater percentage of heroin use days at intake (38.2% dropout at Q1 of 85% use days to 33.3% dropout at Q3 of 97% use days; estimated from 6 studies/12 dropout rates). Dropout as a function of degree of cocaine use at intake was also statistically significant, with 22.4%

Table 2 Participant characteristics subgroup meta-analyses.

Predictor[a]	*Predictor value*	*Studies (dropout rates)*[b]	*Dropout (95% CI)*	*Residual heterogeneity % (P)*	*Test for prediction (P)*
Degree of use, tobacco		55 (108)		92.0 (< 0.0001)	0.8858
	Moderate	1 (2)	27.1 (6.8, 65.2)		
	Heavy	54 (106)	24.8 (20.7, 29.3)		
Degree of use, cocaine		4 (9)		59.7 (0.0206)	0.0173
	Light	1 (1)	22.4 (8.3, 47.9)		
	Moderate	3 (4)	51.8 (36.0, 67.2)		
	Heavy	3 (4)	66.7 (50.6, 79.6)		
Degree of use, cannabis		8 (17)		71.3 (< 0.0001)	0.5511
	Light	2 (5)	32.8 (21.3, 46.7)		
	Moderate	3 (6)	32.9 (22.4, 45.4)		
	Heavy	3 (6)	40.7 (30.1, 52.4)		
Treatment-seeking?		150 (298)		93.6 (< 0.0001)	0.0967
	No or not indicated	8 (20)	30.2 (21.7, 40.3)		
	Yes	140 (272)	31.1 (27.8, 34.5)		
	Mixed	3 (6)	11.4 (4.0, 28.4)		

[a]Subgroup meta-analyses were calculated separately for each variable. Only one predictor value was available for alcohol, and no studies fit the criteria for opioids, methamphetamines, depressants, polysubstance use, hallucinogens, heroin, major stimulants or γ-hydroxybutyric acid (GHB). Forest plots and additional details for each predictor are available in the Supporting Information. [b]The number of studies and study arms included varies by predictor because of variability in reporting among studies. When dropout rates were averaged across study arms, either because of pooled predictors or dropout rates, the study has only a single dropout rate, regardless of how many study arms were included. CI = confidence interval.

dropout for light use (estimated from 1 study/1 dropout rate), 51.8% dropout for moderate use (estimated from 3 studies/4 dropout rates) and 66.7% dropout for heavy use (estimated from 3 studies/4 dropout rates).

Although some other meta-regressions had substantial slopes (e.g. dropout rates of 37–29% between Q1 and Q3 of alcohol drinks per day, $P = 0.0587$; dropout rates of 22.9–31.7% from Q1 to Q3 of polysubstance length of use, $P = 0.2498$), they were limited by study/dropout rate sample size and variability, but may be valuable to consider further in future studies.

Predictors: facilitator characteristics

Tables 4 and 5 display results of a subgroup meta-analysis of facilitator degree and a meta-regression of facilitator years of experience, respectively. As seen in these tables, neither facilitator degree nor years of experience were statistically significantly associated with dropout. However, the substantial slope of facilitator years of experience may warrant future investigation (28.4% dropout at 3 years of experience at Q1 to 40.8% dropout at 10 years of experience at Q3, $P = 0.1025$).

Predictors: treatment characteristics

Tables 6 and 7 show results of subgroup meta-analyses and meta-regressions of treatment characteristic predictors, respectively. As displayed in these tables, dropout rate varied by SUD treatment target. Specifically, rates of dropout were highest for studies that targeted cocaine (48.7%; CI = 38.2, 59.3; estimated from 18 studies/42 dropout rates) and lowest for studies that targeted alcohol (26.1%; CI = 19.1, 34.4; estimated from 21 studies/47 dropout rates) and tobacco (25.5%; CI = 21.4, 30.1; estimated from 65 studies/117 dropout rates). Although the estimated dropout rates were higher for studies targeting methamphetamines (53.5%; CI = 16.5, 87; estimated from 1 study/2 dropout rates) and major stimulants (46.8%; CI = 13.3, 83.4; estimated from 1 study/2 dropout rates) and lower for heroin (25.1%; CI = 8.0, 56.33; 8.0, 56.3; estimated from 2 studies/4 dropout rates), the number of studies and dropout rates were small. In addition, although only one study evaluated treatment in a pregnant sample, pregnancy was associated with a low rate of dropout (pregnant = 4.0%; CI = 0.4,30.1; estimated from 1 study/1 dropout rate; no or not indicated = 30.7%; CI = 27.5, 34.1; estimated from 150 studies/298 dropout rates). Furthermore, studies that included a greater number of treatment sessions (27.5% dropout at Q1 of 7 sessions to 30.2% dropout at Q3 of 14 sessions; estimated from 138 studies/276 dropout rates) and a greater average session length (26.5% dropout at Q1 of 45-minute/session to 31.1% dropout at Q3 of 90-minute/session; estimated from 79 studies/145 dropout rates) were both associated with a higher rate of dropout. Additionally, studies in which a DSM diagnosis was used to confirm presence of SUD for participant inclusion were associated with higher rates of dropout (DSM = 37.0%; CI = 31.9, 42.3; estimated from 68 studies/139 dropout rates; other = 25.7%;

Table 3 Participant characteristics meta-regressions.

Predictor[a]	*Studies (dropout rates)*[b]	*Logit regression*[c]	*Dropout at Q1*[d]	*Dropout at median*[d]	*Dropout at Q3*[d]	*Residual heterogeneity % (P)*	*Test for prediction (P)*
Age (mean years)	146 (294)	−0.1228 − 0.0185X	**34**: 31.9 (28.1, 35.9)	**39**: 30.1 (26.9, 33.4)	**43**: 28.5 (25.0, 32.4)	93.4 (< 0.0001)	0.0916
Sex (proportion male)	145 (289)	−0.9104 + 0.1418X	**0.48**: 30.1 (26.6, 33.9)	**0.60**: 30.5 (27.2, 34.0)	**0.74**: 30.9 (27.1, 35.0)	93.8 (< 0.0001)	0.6593
Education (mean years)	34 (70)	0.9800 − 0.1291X	**12**: 37.7 (29.8, 46.2)	**12**: 35.1 (28.6, 42.3)	**14**: 31.0 (23.5, 39.6)	91.6 (< 0.0001)	0.1556
White (proportion)	112 (225)	−0.4847 − 0.5464X	**0.38**: 33.4 (28.8, 38.3)	**0.64**: 30.3 (26.5, 34.3)	**0.86**: 27.8 (23.2, 32.9)	93.7 (< 0.0001)	0.0607
Hispanic/Latino (proportion)	69 (130)	−0.6818 − 1.0953X	**0.00**: 33.6 (27.7, 40.0)	**0.04**: 32.5 (27.1, 38.4)	**0.15**: 29.9 (25.0, 35.4)	94.8 (< 0.0001)	0.0584
African American (proportion)	74 (142)	−1.2199 + 1.3149X	**0.07**: 24.5 (19.7, 29.9)	**0.28**: 29.8 (25.6, 34.5)	**0.52**: 37.0 (31.1, 43.2)	93.2 (< 0.0001)	0.0004
Other race/ethnicity (proportion)	74 (142)	−0.6745 − 1.3494X	**0.00**: 33.8 (28.4, 39.5)	**0.04**: 32.5 (27.6, 37.9)	**0.08**: 31.2 (26.6, 36.3)	94.1 (< 0.0001)	0.0078
Adjusted mean annual income ($)	16 (34)	−0.1779 − 0.0000X	**9726**: 41.0 (29.1, 54.1)	**15 684**: 38.3 (27.7, 50.1)	**26 670**: 33.5 (24.2, 44.2)	88.4 (< 0.0001)	0.0381
Not married (proportion)	80 (155)	−0.9743 + 0.3732X	**0.56**: 31.7 (26.9, 37.0)	**0.68**: 32.8 (28.3, 37.5)	**0.82**: 33.9 (28.4, 39.9)	93.7 (< 0.0001)	0.4480
Unemployed (proportion)	71 (141)	−0.7961 + 0.2873X	**0.41**: 33.7 (28.1, 39.8)	**0.53**: 34.4 (29.2, 40.1)	**0.74**: 35.8 (28.8, 43.5)	94.6 (< 0.0001)	0.5588
Not unemployed (proportion)	61 (128)	−0.4076 − 0.5058X	**0.28**: 36.6 (29.7, 44.2)	**0.50**: 34.1 (29.0, 39.5)	**0.66**: 32.3 (26.6, 38.7)	93.7 (< 0.0001)	0.2940
Alcohol							
Drinks per day	9 (22)	0.1768–0.0808X	**9**: 37.0 (27.8, 47.1)	**10**: 34.0 (25.8, 43.2)	**13**: 29.0 (20.6, 39.1)	77.6 (< 0.0001)	0.0587
Frequency of use (% days)	19 (40)	−0.3926 − 0.0059X	**26**: 36.7 (24.4, 51.1)	**57**: 32.6 (22.9, 44.0)	**71**: 30.8 (19.5, 45.0)	94.6 (< 0.0001)	0.5072
Length of use (years)	13 (27)	−0.3480 − 0.0011X	**12**: 41.1 (30.7, 52.3)	**15**: 41.0 (31.4, 51.3)	**20**: 40.9 (28.4, 54.6)	92.4 (< 0.0001)	0.9762
Tobacco							
Cigarettes per day	54 (106)	−0.1870 − 0.0420X	**19**: 27.4 (22.5, 32.9)	**22**: 25.1 (21.1, 29.6)	**26**: 21.4 (16.9, 26.9)	91.7 (< 0.0001)	0.0490
Length of use (years)	45 (85)	−1.4013 + 0.0122X	**20**: 23.9 (19.7, 28.7)	**24**: 24.7 (20.7, 29.2)	**26**: 25.4 (21.0, 30.3)	91.5 (< 0.0001)	0.4097
Cocaine							
Frequency of use (% days)	22 (46)	−1.0186 + 0.0176X	**31**: 38.4 (29.1, 48.5)	**44**: 44.1 (33.8, 52.7)	**55**: 48.8 (36.7, 61.0)	92.5 (< 0.0001)	0.0765
Length of use (years)	20 (47)	0.2175–0.0456X	**6**: 48.4 (37.8, 59.3)	**9**: 44.8 (36.1, 53.8)	**12**: 42.2 (32.6, 52.4)	90.1 (< 0.0001)	0.2687
Opioids							
Frequency of use (% days)	6 (16)	−0.3383 + 0.0039X	**31**: 44.6 (37.5, 52.0)	**66**: 48.0 (41.4, 54.7)	**80**: 49.5 (41.3, 57.7)	86.8 (< 0.0001)	0.3161
Length of use (years)	10 (25)	−0.0971 − 0.0420X	**2**: 45.3 (28.2, 63.5)	**9**: 38.1 (25.0, 53.2)	**13**: 34.6 (17.8, 56.5)	94.1 (< 0.0001)	0.4782
Depressants							
Frequency of use (% days)	3 (5)	−0.2067 − 0.0022X	**1**: 44.8 (31.8, 58.5)	**1**: 44.8 (32.0, 58.2)	**2**: 44.8 (32.3, 57.9)	52.2 (0.1160)	0.9417

(*Continues*)

Table 3. (Continued)

Predictor[a]	*Studies (dropout rates)*[b]	*Logit regression*[c]	*Dropout at Q1*[d]	*Dropout at median*[d]	*Dropout at Q3*[d]	*Residual heterogeneity % (P)*	*Test for prediction (P)*
Cannabis							
Frequency of use (% days)	8 (16)	−0.6631 + 0.0033X	**4**: 34.3 (25.6, 44.1)	**40**: 37.0 (30.8, 43.8)	**49**: 37.8 (31.2, 44.8)	76.9 (< 0.0001)	0.4430
Length of use (years)	8 (14)	−0.9316 + 0.0615X	**5**: 35.3 (21.1, 52.7)	**8**: 39.1 (27.4, 52.2)	**10**: 42.4 (28.6, 57.5)	92.9 (< 0.0001)	0.4524
Polysubstance							
Frequency of use (% days)	5 (10)	−0.4997 − 0.0130X	**26**: 30.3 (14.1, 53.5)	**37**: 27.2 (13.3, 47.6)	**39**: 26.8 (12.4, 48.4)	94.4 (< 0.0001)	0.7274
Length of use (years)	4 (7)	−2.4757 + 0.1538X	**8**: 22.9 (12.2, 38.7)	**8**: 23.4 (13.0, 38.5)	**11**: 31.7 (21.3, 44.2)	81.9 (0.0074)	0.2498
Heroin							
Frequency of use (% days)	6 (12)	1.0604–0.0181X	**85**: 38.2 (30.6, 46.4)	**94**: 34.2 (26.4, 43.1)	**97**: 33.3 (25.3, 42.4)	69.5 (< 0.0001)	0.0001
Length of use (years)	8 (17)	0.6815–0.1124X	**8**: 44.0 (25.7, 64.2)	**10**: 40.5 (24.9, 58.2)	**13**: 31.1 (16.5, 50.9)	90.2 (< 0.0001)	0.2393
Comorbid diagnoses							
Mood disorder (%)	23 (49)	−0.4623 − 0.0050X	**14**: 37.0 (28.8, 46.0)	**21**: 36.2 (28.3, 44.9)	**29**: 35.3 (27.6, 43.8)	92.1 (< 0.0001)	0.2395
Anxiety disorder (%)	12 (24)	0.0363 − 0.0216X	**6**: 47.8 (34.8, 61.2)	**14**: 43.6 (33.1, 54.6)	**23**: 38.6 (27.3, 51.2)	89.4 (< 0.0001)	0.2054
Comorbid substance use dependence/ addiction (%)	9 (20)	−0.7248 + 0.0119X	**23**: 39.0 (24.2, 56.0)	**41**: 44.1 (30.1, 59.2)	**52**: 47.3 (31.3, 63.9)	92.1 (< 0.0001)	0.3016
Personality disorder (%)	16 (32)	−0.5608 − 0.0047X	**11**: 35.2 (23.3, 49.3)	**24**: 33.8 (23.8, 45.4)	**42**: 31.9 (22.5, 42.9)	91.8 (< 0.0001)	0.5183
Psychotic disorder (%)	6 (10)	0.4679–0.0184X	**41**: 42.7 (26.8, 60.2)	**47**: 40.2 (25.9, 56.4)	**89**: 23.6 (8.4, 50.8)	89.7 (< 0.0001)	0.2011

[a]Separate meta-regressions were calculated for each predictor. Only one study fit the criteria for frequency of use (% days) for tobacco, methamphetamine and γ-hydroxybutyric acid (GHB), and no studies for hallucinogens and major stimulants; only one study fit the criteria for length of use (years) for methamphetamine, depressants, hallucinogens, major stimulants, and GHB; and only one study fit the criteria for other psychological diagnoses. Meta-regression plots and additional details for all predictors are available in the Supporting Information. [b]The number of studies and dropout rates included varies by predictor because of the variability of reporting across studies. When dropout rates were averaged across study arms, either because of pooled predictors or dropout rates, the study has only a single dropout rate, regardless of how many study arms were included. [c]Because the regression was calculated on the logit scale, the parameter estimates are reported on the logit scale. To use the regression, enter the value of the predictor value of interest, and back-transform to a proportion, such as using the transf.ilogit function in the metafor package in R. [d]Q1, median and Q3 refer to the first quartile, median and third quartile (respectively) of the study-level or study arm-level values of the predictor; note these do not necessarily represent individual participant-level data. Because the regression is on the logit scale, these columns provide interpretable, back-transformed dropout rates in percentage at Q1, median and Q3 predictor values. Data are presented as the bold-type predictor value, followed by the estimated dropout percentage and 95% confidence interval (CI).

Table 4 Facilitator characteristics subgroup meta-analysis[a].

Predictor	*Predictor value*	*Studies (dropout rates)*	*Dropout (95% CI)*	*Residual heterogeneity % (P)*	*Test for prediction (P)*
Degree		82 (158)		93.2 (< 0.0001)	0.2445
	Mixed	36 (71)	33.8 (27.4, 40.8)		
	Bachelors	6 (8)	21.7 (11.1, 38.1)		
	Masters	27 (55)	25.7 (19.6, 32.9)		
	Doctorate	14 (22)	30.2 (20.4, 42.1)		
	Certificate	2 (2)	13.8 (3.0, 44.8)		

[a]A forest plot and additional details are available in the Supporting Information. CI = confidence interval.

Table 5 Facilitator characteristics meta-regression.

Predictor	*Studies (dropout rates)*	*Logit regression*[a]	*Dropout at Q1*[b]	*Dropout at median*[b]	*Dropout at Q3*[b]	*Residual heterogeneity % (P)*	*Test for prediction (P)*
Experience (years)	21 (36)	−1.2013 + 0.0833X	**3**: 28.4 (17.9, 41.8)	**7**: 34.9 (25.0, 46.4)	**10**: 40.8 (28.1, 54.8)	94.6 (< 0.0001)	0.1025

[a]Because the regression was calculated on the logit scale, the parameter estimates are reported on the logit scale. To use the regression, enter the value of the predictor value of interest, and back-transform to a proportion, such as using the transf.ilogit function in the metafor package in R. A plot of the meta-regression and additional details are available in the Supporting Information. [b]Q1, median and Q3 refer to the first quartile, median and third quartile (respectively) of the study-level or study arm-level values of the predictor; note that these do not necessarily represent individual participant-level data. Because the regression is on the logit scale, these columns provide interpretable, back-transformed dropout rates in percentages at Q1, median, and Q3 predictor values. Data are presented as the bold type predictor value, followed by the estimated dropout percentage and 95% confidence interval (CI).

Table 6 Treatment characteristics subgroup meta-analyses.

Predictor[a]	*Predictor value*	*Studies (dropout rates)*[b]	*Dropout (95% CI)*	*Residual heterogeneity % (P)*	*Test for prediction (P)*
Substance being targeted		151 (299)		93.1 (< 0.0001)	0.0050
	Alcohol	21 (47)	26.1 (19.1, 34.4)		
	Tobacco	65 (117)	25.5 (21.4, 30.1)		
	Cocaine	18 (42)	48.7 (38.2, 59.3)		
	Opioids	10 (24)	39.3 (26.6, 53.5)		
	Methamphetamine	1 (2)	53.5 (16.5, 87.0)		
	Cannabis	5 (11)	34.9 (19.4, 54.4)		
	Polysubstance	29 (50)	30.5 (23.9, 38.2)		
	Heroin	2 (4)	25.1 (8.0, 56.3)		
	Major stimulants	1 (2)	46.8 (13.3, 83.4)		
Pregnant participants?		151(299)		93.7 (< 0.0001)	0.0481
	No or not indicated	150 (298)	30.7 (27.5, 34.1)		
	Yes	1 (1)	4.0 (0.4, 30.1)		
Manualized treatment?		148(296)		93.7 (< 0.0001)	0.3268
	No or not indicated	74 (130)	31.9 (27.5, 36.6)		
	Yes	81 (166)	29.1 (25.1, 33.4)		
Setting of trial		151(299)		93.5 (< 0.0001)	0.2672
	Institution	3 (4)	36.8 (16.4, 63.4)		
	Out-patient (hospital/ medical school)	15 (28)	22.8 (15.1, 32.9)		
	Out-patient (public)	113 (227)	32.3 (28.5, 36.3)		
	University-affiliated clinic	12 (26)	25.8 (16.8, 37.4)		
	In-patient	5 (8)	18.4 (8.4, 35.8)		
	Mixed	4 (6)	35.4 (18.4, 57.2)		

(***Continues***)

Table 6. (Continued)

Predictor[a]	*Predictor value*	*Studies (dropout rates)*[b]	*Dropout (95% CI)*	*Residual heterogeneity % (P)*	*Test for prediction (P)*
Pharmacotherapy category[c]		143 (291)		93.4 (< 0.0001)	0.3821
	No	79 (136)	29.7 (25.3, 34.4)		
	Placebo	26 (33)	34.9 (28.1, 42.3)		
	Not agonist	24 (41)	33.6 (26.6, 41.5)		
	Agonist	43 (81)	28.6 (23.4, 34.5)		
Treatment approach		142 (290)		93.4 (< 0.0001)	0.3485
	Cognitive and/or behavioral	72 (121)	28.5 (24.6, 32.8)		
	Motivational	16 (17)	27.7 (20.8, 35.8)		
	Psychodynamic	1 (1)	28.9 (7.3, 67.8)		
	12-Step	3 (4)	38.2 (23.7, 55.3)		
	Integrative	21 (33)	28.9 (22.5, 36.3)		
	Non-specific	74 (114)	32.8 (28.6, 37.4)		
Limited treatment time?		151(299)		93.8 (< 0.0001)	0.2593
	No or not indicated	6 (10)	38.6 (24.7, 54.8)		
	Yes	147 (289)	30.1 (26.9, 33.6)		
Training for fidelity?		150 (298)		93.7 (< 0.0001)	0.7059
	No or not indicated	78 (155)	29.9 (25.7, 34.6)		
	Yes	75 (143)	31.2 (26.6, 36.1)		
Treatment format		149 (297)		93.5 (< 0.0001)	0.0269
	Group	41 (74)	33.2 (27.5, 39.4)		
	Individual	87 (171)	27.1 (23.5, 31.1)		
	Mixed	28 (50)	39.0 (31.4, 47.2)		
	Not specified	1 (1)	12.0 (1.8, 50.9)		
	Couple therapy	1 (1)	29.3 (6.9, 69.8)		
Efficacy study?		151(299)		93.7 (< 0.0001)	0.4196
	Efficacy	134 (277)	29.9 (26.6, 33.5)		
	Effectiveness	17 (22)	34.4 (24.7, 45.5)		
Codification of dependence		151 (299)		93.2 (< 0.0001)	0.0006
	DSM	68 (139)	37.0 (31.9, 42.3)		
	Other	83 (160)	25.7 (22.0, 29.8)		
Country classification		151(299)		93.8 (< 0.0001)	0.4712
	Developed	144 (289)	30.2 (26.9, 33.6)		
	Developing	7 (10)	36.4 (21.3, 54.7)		

[a]Subgroup meta-analyses were calculated for categorical predictor variables. Forest plots and additional details are available in the Supporting Information. [b]The number of studies and study arms included varies by predictor because of variability in reporting among studies. When dropout rates were averaged across study arms, either because of pooled predictors or dropout rates, the study has only a single dropout rate, regardless of how many study arms were included. [c]The active pharmacotherapy category was split into 'not agonist' and 'agonist' *post hoc* at the suggestion of a reviewer.

CI = 22.0, 29.8; estimated from 83 studies/160 dropout rates). Finally, rates of dropout varied by treatment format, being highest for studies using a mixed format (e.g. combination of individual and group counseling; 39.0%; CI = 31.4, 47.2; estimated from 28 studies/50 dropout rates).

DISCUSSION

The purpose of this meta-analysis was to estimate average dropout rates of in-person psychosocial SUD treatment studies and evaluate potential predictors of study dropout. Analyses revealed an average dropout rate of approximately 30% across all SUD treatment studies, which exceeds the average dropout rate of approximately 20% reported in a meta-analysis of adult psychotherapy studies that excluded treatments for SUDs [22]. Although not formally tested herein, one potential reason for increased dropout in psychosocial SUD treatment studies could be elevated behavioral disinhibition among individuals with addiction. Indeed, behavioral disinhibition is a predictor of addiction onset, and addictive substances elicit disinhibitory states acutely during the period of drug action (i.e. during drug 'intoxication') and chronically via changes to cortical regions implicated in cognitive–behavioral control [42–46]. Completing SUD treatment often requires

Table 7 Treatment characteristics meta-regressions.

Predictor[a]	*Studies (dropout rates)*[b]	*Logit regression*[c]	*Dropout at Q1*[d]	*Dropout at median*[d]	*Dropout at Q3*[d]	*Residual heterogeneity % (P)*	*Test for prediction (P)*
Publication year	151 (299)	−3.3093 + 0.0012X	**2000**: 30.3 (26.8, 34.1)	**2006**: 30.5 (27.1, 34.0)	**2009**: 30.5 (26.7, 34.6)	93.7 (< 0.0001)	0.9080
Sessions (*n*)	138 (276)	−1.0991 + 0.0188X	**7**: 27.5 (24.2, 31.1)	**12**: 29.5 (26.3, 32.8)	**14**: 30.2 (27.1, 33.6)	93.0 (< 0.0001)	0.0016
Session length (minutes)	79 (145)	−1.2494 + 0.0050X	**45**: 26.5 (22.5, 30.9)	**60**: 28.0 (24.0, 32.2)	**90**: 31.1 (26.4, 36.2)	92.8 (< 0.0001)	0.0122
Treatment window (weeks)	138 (275)	−0.8212 + 0.0020X	**8**: 30.9 (27.4, 34.7)	**12**: 31.1 (27.7, 34.6)	**14**: 31.1 (27.8, 34.6)	93.3 (< 0.0001)	0.6628

[a]Separate meta-regressions were calculated for each continuous predictor. Meta-regression plots and additional details are available in the Supporting Information. [b]The number of studies and dropout rates included varies by predictor because of the variability of reporting across studies. When study arms were averaged because of pooled predictors or dropout rates, the study has only a single dropout rate. [c]Because the regression was calculated on the logit scale, the parameter estimates are reported on the logit scale. To use the regression, enter the value of the predictor value of interest, and back-transform to a proportion, such as using the transf.logit function in the metafor package in R. [d]Q1, median and Q3 refer to the first quartile, median and third quartile (respectively) of the study-level or study arm-level values of the predictor; note these do not necessarily represent individual participant-level data. Because the regression is on the logit scale, these columns provide interpretable, back-transformed dropout rates in percentages at Q1, median and Q3 predictor values. Data are presented as the bold type predictor value, followed by the estimated dropout percentage and 95% confidence interval (CI).

long-term planning and persistence, both of which may be challenging to individuals prone to impulsivity and difficulties with cognitive–behavioral regulation.

Analyses also identified a number of predictors of dropout. In an attempt to make sense of these findings, speculative hypotheses are provided for further examination in future research. Studies including a higher percentage of African Americans and lower-income individuals were associated with higher dropout rates. One hypothesis for these associations may be the lack of culturally relevant treatment components (cf. [47,48]). The ecological validity model (EVM [49]) is recommended as a guide to culturally adapt interventions across eight dimensions (language, people, metaphors, content, concepts, goals, methods and context). EVM-based cultural adaptation has been shown to provide positive outcomes for parenting interventions (e.g. [50]), but the effects on treatment dropout have not been established.

With regard to SUD-specific variables, studies that included individuals who reported a greater number of cigarettes smoked per day at intake and greater percentage of heroin use days at intake were both associated with lower rates of dropout. These results may reflect greater treatment engagement among those with greater perceived treatment need [51]. Conversely, studies that included individuals who reported a heavier degree of cocaine use at intake were associated with higher rates of dropout. In addition, rates of dropout were highest for studies that targeted cocaine, methamphetamines and major stimulants (broadly defined) and lowest for studies that targeted alcohol, tobacco and heroin. That use of major stimulants, including cocaine, would be especially associated with dropout is supported by a number of lines of evidence. First, an expert panel evaluating 20 drugs of abuse via multi-criteria decision analysis rated major stimulants as having among the greatest dependence potential and impairment on mental functioning [52]. Second, major stimulant use may be associated more with risky sexual behavior than other drug use [53], which suggests a particularly robust relationship with impulsivity. Indeed, in a study of more than 25 000 individuals under community corrections supervision, cocaine use disorder was the strongest predictor of supervision failure among 15 predictors that also included cannabis use disorder, alcohol use disorder and opiate use disorder, among other SUDs [54]. Third, there are no approved pharmacotherapies for major stimulant dependence, exacerbating withdrawal distress that may complicate treatment completion [55]. Finally, contingency management appears to be the most effective of psychosocial interventions for major stimulant use. This suggests a strong need for competing incentives among users of major stimulants that may not be met by most treatments [55,56].

Studies that included a greater number of treatment sessions and greater average session length were both associated with a higher rate of dropout. This presents a conundrum, as the length of successful, engaged treatment improves SUD outcomes [57]. Brief treatments are associated with lower dropout rates, yet may potentially be less effective. Of course, treatments involving more and longer sessions provide more opportunities to drop out. Less traditional approaches, such as engaged mobile or remote methods, should be further investigated, as they may reduce participant burden while not significantly altering the content of treatment. Nevertheless, we do not advocate here for fewer and briefer sessions in the treatment of SUD. Rather, there may be a 'Goldilocks zone' with regard to number of treatment sessions and session length, wherein dropout is minimized and efficacy is maximized. This is a question for future research.

There were other predictors, such as treatment format and codification of dependence, that were shown to be associated with dropout. Further research could help to understand more clearly the mechanisms underlying these relationships. Further research could also evaluate potential predictors of dropout infrequently reported and therefore not assessed in the current meta-analytic review. For example, with regard to participant characteristics, greater ambivalence toward treatment may be associated with higher rates of dropout [58,59]. With regard to facilitator characteristics, stronger therapeutic alliance may predict a reduced likelihood of dropout [60], and with regard to treatment characteristics, psychosocial interventions that elicit feedback from participants/clients may produce lower dropout rates [61,62], as may those that engage in directed interventions designed to minimize this outcome (e.g. [63]). Future research should test the relationships between these characteristics, among others, and psychosocial SUD treatment dropout.

Limitations

Inconsistency in the reporting of participant, facilitator and treatment characteristics in the original studies included in our analysis limited our ability to analyze and interpret some of our predictors. For instance, several estimates were unable to be computed because too few studies reported on the same constructs, and in other cases, few studies reported the same constructs in a similar manner (e.g. in the reporting of income by individual versus household, reporting education in years versus level-attainment), leading to reduced power to detect associations.

Because some of the meta-regressions used summaries of participant characteristics, such as testing the associations between race and dropout rates, it raises the potential for a form of 'ecological fallacy'. For example, although dropout increased as the proportion of African American participants increased, it could be that non-African American participants accounted for increased dropout in these studies. Such potential confounders could be investigated further if individual participant data were pooled.

As is common of summaries of clinical trials, external validity might be limited because many of the clinical trials included in these analyses were conducted in controlled settings designed to test efficacy under ideal conditions that maximize internal validity. However, it is noted that dropout rates did not differ between efficacy trials focused on internal validity and effectiveness trials designed to more closely approximate real-world treatment contexts. Furthermore, research conducted in the psychological laboratory generally produces externally valid results [64], which is generally supportive of the external validity of psychosocial SUD interventions, and randomized clinical trials remain the gold standard for evaluating safety and efficacy despite challenges to external validity [65]. Nevertheless, the current results are unlikely to completely generalize to all real-world populations and settings. Clinical judgement is required to determine the relevance of the present findings to real-world practice. Such judgement requires information concerning the settings of the trials, selection and characteristics of participants and differences between study protocols and real-world practice, among other factors [66].

Future research

Future research can build upon this work to understand more clearly how to reduce or predict dropout. Recent work has evaluated directed interventions to prevent dropout (e.g. [63]) and further efforts are encouraged. An inductive approach was used to gather and analyze the data. Future analyses could focus on gaining a clearer understanding of what is predictive and causative in order to reduce dropout. Such research could potentially take a hypothesis-driven, intersectional approach to analyzing predictors. For example, future research could investigate interactions among specific participant, facilitator and treatment characteristics to understand more clearly determinants or associations with dropout. We have made the data available to encourage other investigators to probe hypotheses of interactions among predictors evaluated herein. Because of the high remaining heterogeneity, we acknowledge that our models do not sufficiently explain differences in dropout rates among studies. For instance, it may be that the associations between race and dropout rate differ among treatments for different SUDs. Rather than attempting to probe all possible predictor combinations herein, thereby risking high rates of false associations

(there are thousands of pairwise associations possible among variables, let alone the categories some of those variables can take), we encourage readers to probe hypothesis-driven associations to answer targeted questions.

Additionally, we call for improving the quality and comprehensiveness in the reporting of clinical trials of psychosocial SUD treatment, particularly with respect to dropout rates as well as participant, facilitator and treatment characteristics. At a minimum, authors should use best-practice reporting guidelines, such as the Consolidated Standards for Reporting Trials (CONSORT [67]) guidelines, or its extensions, such as CONSORT for Participant Reported Outcomes [68]. Table 1 of this paper could serve as a guide for future clinical trials. In addition, our data were limited by the lack of complete reporting of important characteristics concerning the participants, the facilitators or the treatment itself. Even when such elements were reported, they were frequently averaged across all study arms instead of reported separately for each arm. Sharing individual participant data where possible would allow even more power and flexibility to investigate characteristics that may be correlated with propensity for dropout. Steps to improve research rigor, reproducibility and transparency have been called for in science generally [69], and we believe these are also apt for psychosocial SUD treatment.

CONCLUSIONS

This is the first meta-analysis, to our knowledge, that investigates dropout of in-person psychosocial treatment for SUDs. The results can be used to establish a base dropout rate against which existing and new treatments can be compared, allow for more careful planning of clinical trials with respect to dropout expectations and determine which populations or study design characteristics might be at elevated risk for dropout. Future research can focus on understanding the interactions between various treatment components (i.e. participant characteristics, facilitator characteristics and treatment characteristics) that may contribute to dropout, and design treatments that decrease the likelihood of dropout.

Declaration of interests

None.

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