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Psychotherapy dropout: a bibliometric analysis

Lei Zhang[1] · Joshua K. Swift[2] · Yan-tong Wan[3] · Jun-wu Hu[1] · Xin Zhang[1] · Xi-yuan Sun[1] · Xiao-yuan Zhang[1] · Yan-fei Hou[4]

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Abstract
Psychotherapy dropout represents a persistent challenge in mental healthcare delivery. This study presents the first comprehensive bibliometric analysis mapping the intellectual structure and evolution of dropout research, utilizing 861 publications indexed in the Web of Science Core Collection from 1961 to 2024. Employing performance analysis and science mapping techniques, including citation analysis, keyword co-occurrence, and burst analysis, we identified key developmental trajectories, thematic hotspots, and emerging frontiers. Results indicate a consistent growth in research output, largely quantitative in nature and predominantly led by the United States. Key research hotspots include dropout within specific clinical populations (particularly post-traumatic stress disorder, eating disorders, and substance use disorders), the extensive focus on dropout related to Cognitive Behavioral Therapy (CBT), and the pivotal role of the therapeutic alliance, highlighting the need for tailored retention strategies. Notably, the application of machine learning for predicting dropout emerged as a significant and rapidly advancing research frontier. This data-driven overview underscores critical needs for future research, including refining dropout's operational definition, integrating qualitative methodologies to complement quantitative findings, increasing focus on real-world effectiveness studies, and enhancing cross-cultural perspectives beyond Western, Educated, Industrialized, Rich, and Democratic contexts. This bibliometric analysis provides valuable guidance for researchers and clinicians aiming to address psychotherapy retention challenges and improve treatment outcomes.

Keywords Psychotherapy · Dropout · Attrition · Premature termination · Bibliometric analysis

Psychotherapy dropout: a bibliometric analysis

"Psychotherapy dropout" refers to the phenomenon where a client initiates therapy but discontinues before the issues that prompted them to seek therapy (including symptoms, functional impairment, and distress, etc.) are resolved (Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993). In psychotherapy research, terms such as "dropout," "attrition," "premature discontinuation," "premature termination," "unilateral termination," "early withdrawal," and "early termination" are often used interchangeably, although they highlight different nuances. For instance, "dropout" is a general term for clients ending therapy without formally completing the treatment program, while "attrition" is broader, often used in research to describe participant loss over time for various reasons. Terms like "premature" or "early" emphasize timing indicate that therapy ended sooner than planned or deemed appropriate. "Unilateral termination"

✉ Xiao-yuan Zhang
zhxy@smu.edu.cn

✉ Yan-fei Hou
simahyf2118@smu.edu.cn

[1] Department of Psychology, School of Public Health, Southern Medical University, 1838 Guangzhou Road, Guangzhou, Guangdong 510515, China

[2] Department of Psychology, Stop 8112, Idaho State University, 921 S. 8th Ave, Pocatello, ID 83201, USA

[3] Guangdong Provincial Key Laboratory of Proteomics, Department of Pathophysiology, School of Basic Medical Sciences, Southern Medical University, Guangzhou, China

[4] School of Nursing, Southern Medical University, 1838 Guangzhou Road, Guangzhou, Guangdong 510515, China

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refers to the client's decision to stop therapy without mutual agreement with the therapist, often signaling a more abrupt end to the therapeutic process, whereas "withdrawal" highlights the client's active decision to exit therapy earlier than expected (He et al., 2020; Swift & Greenberg, 2015).

Psychotherapy dropout is a pervasive issue. Wierzbicki & Pekarik's (1993) seminal meta-analysis reported an average dropout rate of 46.86% (*SD*=22.25, 95% CI [42.9%, 50.82%]). Nearly two decades later, a subsequent comprehensive meta-analysis by Swift & Greenberg (2012) provided an updated weighted dropout rate of 19.7% (95% CI [18.7%, 20.7%]). Although this more recent estimate is lower, it still represents a significant challenge for the field, especially as current research highlights varied rates in specific populations, such as 25.6% among U.S. military veterans (Penix-Smith et al., 2024). Further, it can also engender a cascade of negative consequences for therapists, service-providing institutions, and society at large. For instance, for therapists, it can lead to feelings of frustration and burnout; for institutions, it results in the inefficient allocation of clinical resources and longer waiting lists; and for society, it contributes to higher long-term healthcare costs and reduced productivity due to unresolved mental health issues (Swift & Greenberg, 2015). Addressing psychotherapy dropout is therefore critical to improving treatment outcomes and optimizing mental health service delivery.

Research on psychotherapy dropout spans three primary domains. First, many studies examine dropout as one of several therapeutic outcomes. In this research, dropout is not the main focus but is analyzed alongside other variables. Second, some studies specifically investigate the causes, predictors, and prevention of dropout. Third, reviews and meta-analyses synthesize findings from the literature. While these works provide valuable insights, they often lack a comprehensive perspective of the literature on the phenomenon as a whole, due to the criteria used to select studies for inclusion and the scope of the literature they examine (Donthu et al., 2021).

In this context, bibliometric analysis can serve as a powerful methodological tool. This systematic and quantitative method provides a synthesis and visualization of academic literature through co-occurrence analysis, citation analysis, keyword analysis, and other related approaches. Unlike traditional reviews, bibliometric analysis provides a holistic view of the intellectual structure and evolution of research fields. Bibliometric analysis offers a powerful methodological tool for systematically synthesizing and visualizing academic literature, enabling the identification of influential contributors, research hotspots (areas of high research activity), and intellectual frontiers within a field, ultimately offering a data-driven roadmap for future research (Öztürk et al., 2024). Leveraging this approach, the present study aims to provide a comprehensive overview of the psychotherapy dropout research landscape by addressing two pivotal research questions (RQs):

RQ1: What are the publication trends and who are the major contributors (countries, institutions, authors, journals) in psychotherapy dropout research?
RQ2: What are the research hotspots and frontiers within the psychotherapy dropout literature?

By systematically applying performance analysis and science mapping techniques, this study seeks to provide data-driven answers to these research questions, thereby deepening our understanding of the evolution and current state of this critical research domain.

Materials and methods

Data collection

The Web of Science (WoS) database was selected as the data source for this bibliometric analysis due to its stringent journal-inclusion criteria, unified metadata schema, and selective coverage of high-impact literature, which collectively promote consistency and reliability in citation metrics (Singh et al., 2021). Alternative sources such as Scopus and Google Scholar, despite offering broader coverage, demonstrate heterogeneous indexing protocols and variable metadata quality, potentially introducing comparability issues and duplication biases(AlRyalat et al., 2019; Öztürk et al., 2024). Restricting the dataset to WoS thus enhances methodological transparency, reproducibility, and comparability, aligning with the study's aim to evaluate core scholarly influence rather than maximize publication volume.

The search strategy was carefully designed, referencing retrieval approaches from prior reviews and meta-analyses (Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993). We aimed to balance "comprehensiveness" and "precision" to retrieve all relevant literature on psychotherapy dropout. The specific search queries are shown in Fig. 1. The search was finalized on September 16, 2024, and was limited to articles and reviews in English to enable in-depth content analysis. This process identified 861 publications, comprising 793 articles and 68 reviews. Full records and cited references for each publication were downloaded in plain text format from the Web of Science Core Collection (WoSCC) database. The extracted data included publication details, research categories, country/institution information, author/co-author lists, journal names, reference lists, and keywords.

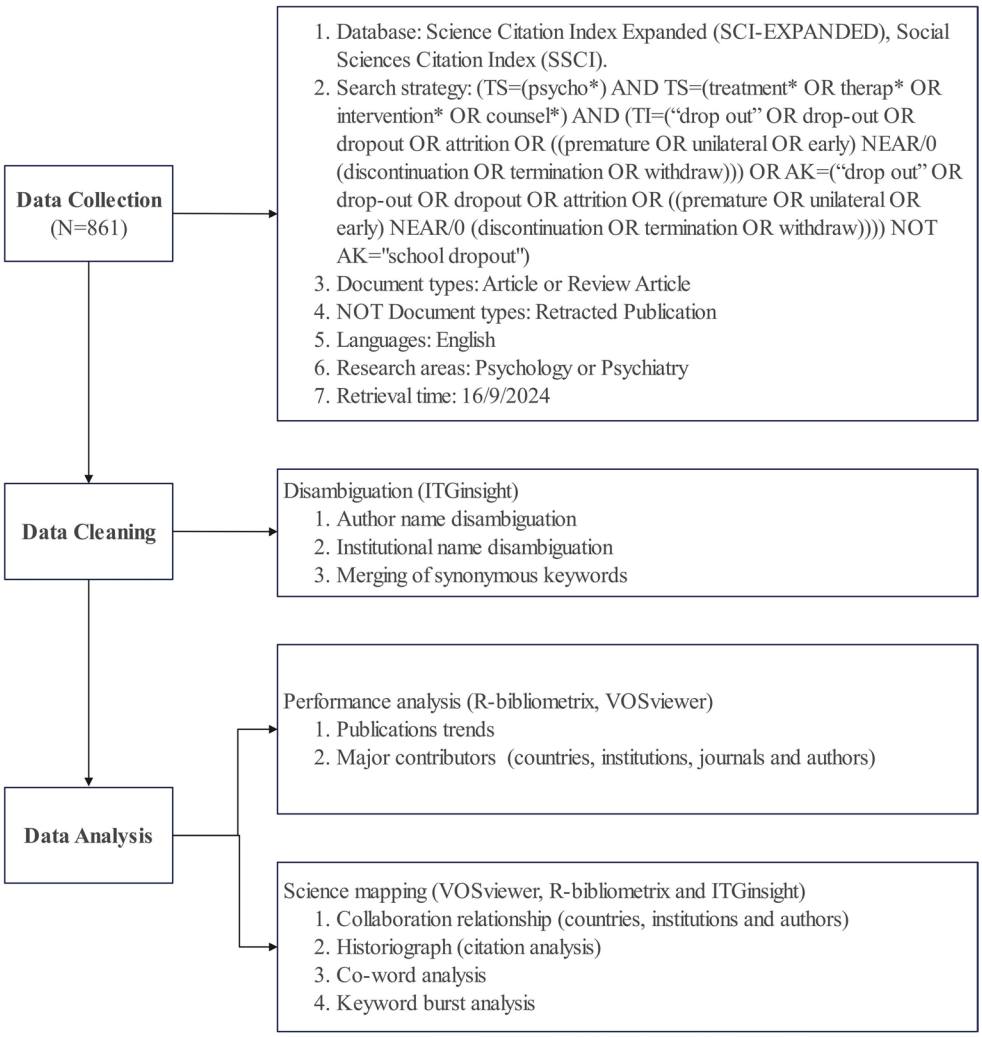

Fig. 1 Study flow chart

Data cleaning

Raw bibliometric data often requires cleansing and processing to ensure accurate analytical outcomes (Xu et al., 2022). ITGInsight was used to automate the data cleaning process, resolving ambiguities and standardizing author names, institutional names, and synonymous keywords. Additionally, ITGInsight generated reusable dictionaries from the cleansed data, enhancing research efficiency and consistency. These dictionaries can be converted into compatible formats for use with other tools, such as VOSviewer and R-bibliometrix, broadening the scope of analysis (Wang et al., 2021). By adopting these methodologies, we ensured the reliability of our analytical results.

Data analysis

Performance analysis and science mapping are two core methods in bibliometrics. Performance analysis quantitatively evaluates contributions and impacts within a research field, examining metrics like publication counts, citation numbers, and h-index to assess the scientific output and influence of researchers, institutions, countries, and journals. Science mapping focuses on visualizing the intellectual structure and network relationships within a research field to reveal collaboration patterns, knowledge structures, research hotspots, and emerging trends (Donthu et al., 2021; Öztürk et al., 2024).

In this study, we integrated performance analysis and science mapping to comprehensively address our research questions. To address RQ1 (Publication Trends and Major Contributors), we utilized performance analysis metrics derived from the dataset (e.g., annual publication counts, citation data) and employed tools such as R-bibliometrix and VOSviewer for identifying and visualizing the most influential countries, institutions, authors, and journals, as well as mapping collaboration networks. Basic trend visualization (e.g., combined bar and line charts) was created using Excel. To address RQ2 (Research Hotspots and Frontiers), we applied science mapping techniques. Specifically,

citation analysis, term frequency analysis, co-word analysis (keyword co-occurrence clustering), and keyword burst analysis were conducted using R-bibliometrix, VOSviewer, and ITGInsight to uncover the intellectual structure, identify thematic research hotspots, and detect emerging trends and frontiers within the psychotherapy dropout literature (Aria & Cuccurullo, 2017; van Eck & Waltman, 2010; Wang et al., 2021). This dual approach allowed for both a quantitative overview of the field's development and contributors, and an in-depth exploration of its thematic content and future trajectory.

Results

Publication trends and major contributors

From 1961 to 2024, a total of 3470 authors contributed 861 papers, published across 240 journals (Supplementary Table 1, Supplementary Fig. 1). Among these publications, primary literature accounted for 733 papers, while secondary literature, including 68 reviews and 60 meta-analyses, constituted 128 papers. Within the primary literature, quantitative research dominated with 614 papers, followed by qualitative research with 115 papers, and mixed methods research with only 4 papers. The overall publication output demonstrates a consistent upward trajectory, exhibiting an annual growth rate of 5.6%, with research activity peaking in 2021.

The 861 publications originated from 52 countries, with Supplementary Table 2 highlighting the top ten countries by publication output. The United States led with 422 publications (49.01%), followed by the United Kingdom with 99 publications (11.50%). Figure 2a presents a collaboration network diagram for countries with at least five publications. The United States has the strongest collaboration network (TLS = 154), followed by the Netherlands (TLS = 94) and Italy (TLS = 91). Supplementary Fig. 2 displays an overlay visualization map of countries, with yellow nodes indicating that research outputs from Portugal, Brazil, Colombia, and Northern Ireland, among others have been concentrated in recent years.

A total of 1,161 institutions have contributed to the psychotherapy dropout literature, with the top ten institutions by publication output listed in Supplementary Table 3. The University of Pennsylvania was leading with 31 publications, followed by Yale University with 18. Figure 2b illustrates a collaboration network diagram for institutions with at least five publications. The University of Pennsylvania is the most active in the network (TLS = 114), followed by Columbia University (TLS = 68) and Duke University (TLS = 67). Supplementary Fig. 3 highlights institutions with more recent contributions to the field. Notable examples include the University of Trier (average publication year, APY = 2021) and the National Center for PTSD (APY = 2020).

Supplementary Table 4 lists the top 10 most influential researchers in the field of psychotherapy dropout research. Swift J. K., was leading in H-index, total publications, and local citation counts, demonstrating a significant impact within the domain; his work is characterized by comprehensive meta-analyses and the development of strategies to reduce premature termination (Swift & Greenberg, 2015). Among the distinguished researchers, Kazdin, A. E., with a publication year start of 1990 (PY-start = 1990), was recognized as one of the pioneering investigators in this field, with a particular focus on attrition in child psychotherapy (Kazdin et al., 1997). Lutz, W., whose initial research in this area was published in 2017 (PY-start = 2017), represents a scholar with emerging contributions, often applying machine learning algorithms to predict patient dropout (Bennemann et al., 2022; Duhne et al., 2022). Figure 2c illustrates the collaboration between authors, with 108 nodes forming 20 clusters, 267 links, and a total link strength of 554. Overall, there was close collaboration within each cluster, but relatively less collaboration between clusters. Three clusters had more than 10 members. First, the red cluster (e.g., Granero, R.; Fernández-Aranda, F.) focused on psychotherapy dropout among individuals with eating disorders, gambling addiction, and compulsive buying behaviors. Second, the green cluster (e.g., Thase M. E.; Rush, A. J.) addresses treatment dropout issues among patients with depression. Third, the blue cluster (e.g., Stirman, S. W.; Spoont, M. R.) investigates dropout in post-traumatic stress disorder (PTSD) treatment, particularly among veterans. Supplementary Fig. 4 indicates that the PTSD research team's output is concentrated around 2021, suggesting that the dropout issue in PTSD psychotherapy for veterans has gained attention in recent years.

Supplementary Table 5 lists the top 10 most influential journals in the field of psychotherapy dropout research. Overall, *Psychotherapy* was the leading journal in this field, with a local H-index of 21, 30 articles, and 693 local citations. The *Journal of Consulting and Clinical Psychology* ranked second (local H-index = 14, NP = 18), but had the highest number of local citations (1924) among all journals. This prominence is clearly reflected in Fig. 2d, where the journal's area shows the highest density. Close behind was *Psychotherapy Research* (local H-index = 14, LC = 581), with the highest number of publications (32) in this field.

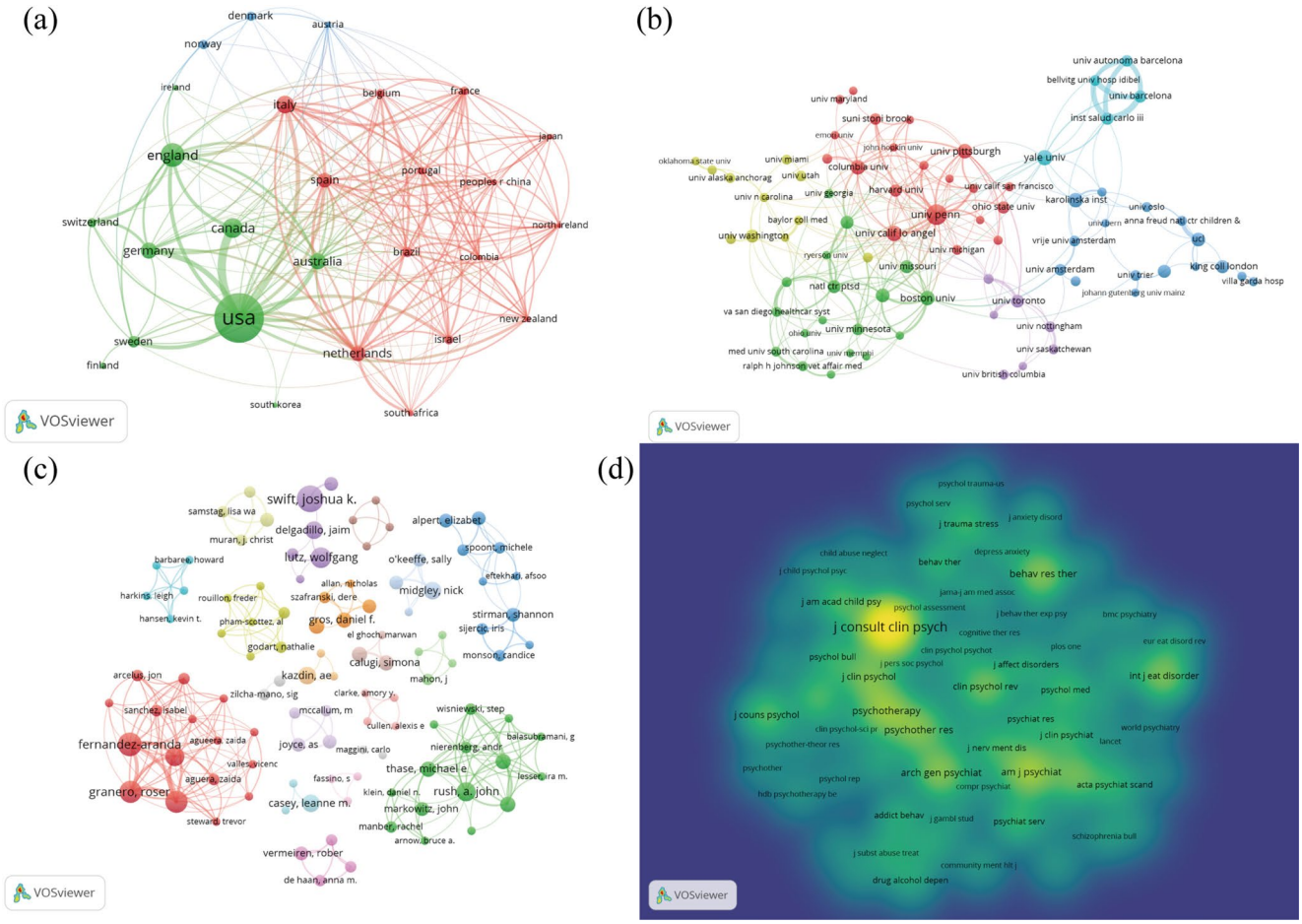

Fig. 2 Analysis of countries, institutions, authors and journals. (**a**) Network visualization map of dropout research across countries (**b**) Collaboration map of dropout research by institutions (**c**) Collaboration map of authors conducting dropout research (**d**) Density visualization map of journals publishing dropout research. In Figures a, b, and c, each node represents an analyzed entity, and the size of the node indicates the number of publications. The lines connecting the nodes represent collaborative relationships, and the thickness of the lines (link strength) reflects the frequency of collaboration. Different colors represent different groups, and the collaborative relationships within each group are closer. In Figure d, the lighter the color, the larger the number of publications in the journal

Articles

Figure 3a presents a historiograph visualizing the citation relationships among highly cited articles throughout the entire study period (1961–2024), with isolated nodes removed. The diagram includes 55 documents exceeding 14 local citations, arranged chronologically from left to right. Circles represent articles, with sizes proportional to their local citation counts, and lines indicate citation links. This visualization offers insights into the core literature, research evolution, and intellectual milestones within the psychotherapy dropout field. For instance, the historiograph marks a clear timeline of influence, beginning with early foundational studies like Trepka (1986) on patient attrition, visible on the far left of the network. It then charts the emergence of pivotal meta-analyses that synthesized the field's knowledge, such as those by Wierzbicki & Pekarik (1993) and Swift & Greenberg (2012), which are represented as major, highly-connected nodes. Furthermore, the map illustrates the field's continued evolution toward specific, high-priority clinical areas, exemplified by the recent and highly-cited meta-analysis on PTSD treatment dropout by Lewis et al. (2020), which aligns with our finding that PTSD represents a major contemporary research hotspot.

Supplementary Table 6 lists the ten most locally cited documents overall, which are also represented by larger circles in Fig. 3a. Eight of these are secondary research, such as meta-analyses or literature reviews. The top three most-cited documents include two pivotal meta-analyses and one influential review that comprehensively summarized the field by reporting dropout rates, analyzing dropout reasons, and proposing reduction strategies, thus garnering high citation counts (Barrett et al., 2008; Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993). Two other highly-cited reviews (ranked 5th and 10th locally) specifically synthesized dropout reduction strategies, such as enhancing

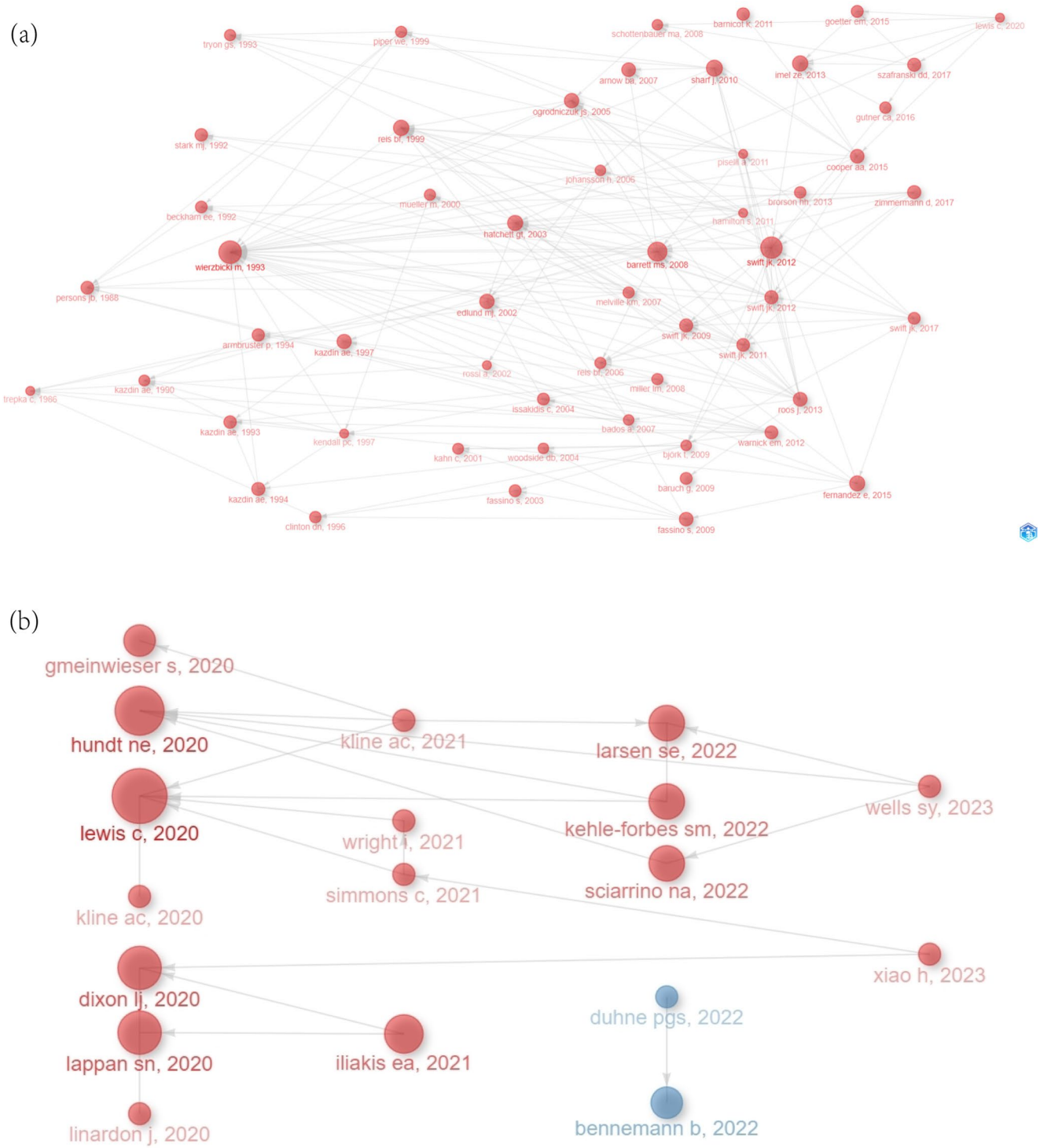

Fig. 3 Citation analysis of articles (**a**) Historiograph of dropout articles (1961–2024) (**b**) Historiograph of dropout articles (2019–2024)

perspective convergence within the therapeutic dyad and employing pre-treatment preparation procedures (Ogrodniczuk et al., 2005; Reis & Brown, 1999). Furthermore, three meta-analyses (ranked 4th, 6th, and 8th) focused respectively on the relationship between dropout and the therapeutic alliance (Sharf et al., 2010), post-traumatic stress disorder (PTSD) (Imel et al., 2013), and cognitive behavioral therapy (CBT) (Fernandez et al., 2015). These themes also emerge as prominent topics in the subsequent keyword analysis, suggesting their centrality to the field.

The remaining two documents in the top ten (ranked 7th and 9th) were the only primary studies. The former compared four different operational definitions of psychotherapy dropout, concluding they represent distinct constructs and should not be used interchangeably (Hatchett & Park, 2003). The latter, analyzing epidemiological survey data from the US and Ontario, found dropout rates between 17 and 19% and identified low income, younger age, lack of insurance, negative treatment attitudes, and single-modality treatment as key predictors (Edlund et al., 2002).

Focusing on recent influential work, Supplementary Table 7 highlights the ten most locally cited documents from the past five years (2019–2024). Half of these publications centered on PTSD, a finding consistent with patterns observed in the author overlay visualization map and keyword analysis, indicating heightened recent research interest in this area. The most highly cited document during this period was a meta-analysis by (Lewis et al., 2020), which reported an average dropout rate of 16% for psychological therapies targeting PTSD, albeit with significant heterogeneity across studies. This study found higher dropout rates associated with trauma-focused therapies compared to non-trauma-focused therapies, while rates did not significantly differ based on therapy format, recruitment source, participant demographics, or educational background.

Emerging methodological approaches are also evident. Figure 3b highlights a distinct blue cluster featuring two recent studies that employed machine learning techniques to predict psychotherapy dropout. Duhne et al. (2022) utilized machine learning to predict early dropout in low-intensity psychological interventions, suggesting that tailored treatment allocation could enhance engagement and outcomes. Similarly, Bennemann et al. (2022) employed nested cross-validation to evaluate various machine learning algorithms, identifying an ensemble of Random Forest and nearest-neighbor modeling as optimal for predicting patient dropout from CBT, with education level, age, and specific inventory scores emerging as key predictors.

Keywords

In bibliometric research, keyword analysis constitutes a pivotal method for identifying research hotspots and emerging trends. Supplementary Table 8 lists the 20 most frequent keywords, while Fig. 4a illustrates their co-occurrence relationships. The search terms "dropout," "attrition," "psychotherapy," "premature termination" and "treatment" exhibited substantially higher frequencies than other keywords and co-occurred broadly, posing a potential bias to clustering outcomes; consequently, these high-frequency terms were excluded and the remaining 60 keywords with occurrence counts exceeding six were subjected to clustering via VOSviewer.

The analysis revealed seven color-coded clusters that delineate the multidimensional foci of psychotherapy dropout research. Cluster 1 (light red), characterized by keywords such as schizophrenia and psychosis, focuses on premature termination among patients with schizophrenia and related psychotic disorders. Cluster 2 (dark green), centered on depression, anxiety disorders, personality disorders, and the therapeutic alliance, examines treatment adherence in patients with depression and comorbid anxiety and the influence of alliance and motivation on dropout. Cluster 3 (cobalt blue), emphasizing adolescents and borderline personality, investigates engagement and dropout issues in adolescent borderline personality disorder populations. Cluster 4 (yellow), encompassing substance use disorder, retention, relapse, and women, analyzes retention and dropout mechanisms in substance use populations, particularly female patients. Cluster 5 (purple), including cognitive behavioral therapy (CBT), treatment outcome, predictors, and machine learning, reflects studies on intervention efficacy—especially CBT—and dropout risk prediction using statistical and machine learning models. Cluster 6 (light blue), focusing on eating disorders, anorexia nervosa, bulimia nervosa, and expectations, addresses adherence and treatment interruption among patients with eating disorders. Finally, Cluster 7 (bright orange), comprising PTSD, prolonged exposure, and veterans, investigates dropout in PTSD interventions, particularly among veterans. Collectively, these clusters map the literature's emphasis across diverse clinical populations, diagnostic categories, therapeutic modalities and predictive variables, thereby providing a theoretical basis for the development of tailored interventions and preventive strategies.

Burst term analysis identifies keywords that have experienced a sharp increase in frequency during specific time periods, thus highlighting emerging research trends and focal points within the literature. Figure 4c displays the top 25 keywords exhibiting the strongest frequency bursts between 2000 and 2024. In the figure, keywords are listed vertically on the left. Adjacent to each keyword, the number shown in brackets indicates the calculated burst strength (e.g., 'dropout' [0.1269]), signifying the intensity of the frequency increase. The years listed next to the strength value indicate the start and end year of the detected burst period for that keyword. The horizontal red bars visually represent the duration of this burst period for each keyword against the timeline presented across the top of the figure. A higher burst strength value suggests a more pronounced surge in the keyword's usage during its active period.

Except for "dropout," most burst terms appeared briefly and did not persist. The only keyword with ongoing appearances in recent years was "machine learning" (related to Cluster 5 focusing on predictors), signifying its importance as a hot topic and cutting-edge direction in psychotherapy

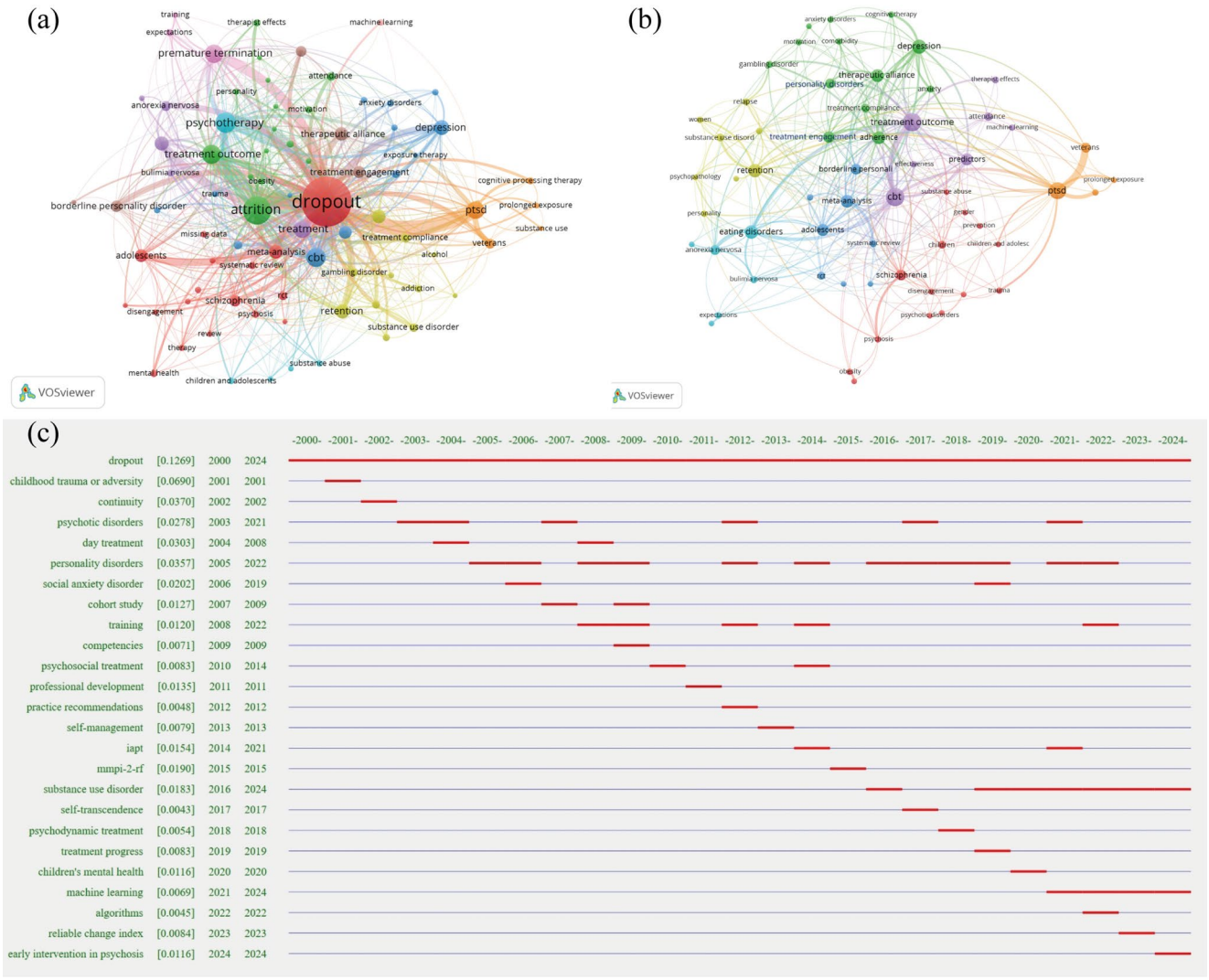

Fig. 4 Analysis of keywords (**a**) Network map of keywords in the dropout field (**b**) Network map of keywords in the dropout field (search terms excluded) (**c**) Top 25 keywords with the strongest strength of burst

dropout research. This trend is further evidenced by the emergence of related terms, such as "algorithms" in 2022. Additionally, "substance use disorder (SUD)" emerged as a burst term in 2016, indicating sustained research interest in this population. Beyond these more persistent themes, other recent burst terms highlight emerging interest in specific topics, such as "reliable change index" (2023) and "early intervention in psychosis" (2024).

Discussion

Publication trends and major contributors

The bibliometric analysis reveals a steadily growing body of research on psychotherapy dropout originating as early as 1961, indicating sustained and increasing global attention to this critical issue. Furthermore, our analysis of the literature composition highlights a notable characteristic: within the primary research, quantitative studies ($n = 614$) significantly outnumber qualitative ($n = 115$) and mixed-methods ($n = 4$) investigations. While quantitative approaches are invaluable for identifying patterns and the extent of phenomena in dropout research, the complexity of why individuals discontinue therapy prematurely often necessitates qualitative methods to explore subjective experiences and nuanced contextual factors in greater depth.

The United States is the dominant leader in this field, ranking first in publication volume, citation frequency, and international collaboration, consistent with the findings by Zhang et al. (2017), showing that the majority of psychiatry publications originated from the U.S. While collaboration

exists, fostering more targeted partnerships between high-resource and low-resource settings could be crucial for diversifying perspectives on dropout, adapting interventions cross-culturally, and ensuring findings are relevant beyond Western, Educated, Industrialized, Rich, and Democratic (WEIRD) contexts(Muthukrishna et al., 2020; Pitesa & Gelfand, 2023).

The identification of key institutions and prolific authors, such as the University of Pennsylvania and Swift J.K. respectively, highlights the influential centers and researchers shaping the discourse. Understanding these core contributors and their collaborative networks can be valuable for researchers seeking collaboration or aiming to track the evolution of theoretical models and intervention strategies within the field. The presence of both pioneering figures like Kazdin A.E. and more recent high-impact scholars like Lutz W. reflects the field's longevity and continued dynamism.

Specialized psychotherapy journals, such as *Psychotherapy* and *Psychotherapy Research*, were the primary outlets for this research. Notably, the prominence of journals focused on specific conditions—such as eating disorders—among the top-ranked outlets suggests that dropout is perceived as a particularly pressing clinical issue in these areas, thereby warranting concentrated research attention.

Research hotspots and frontiers

The bibliometric analysis conducted in this study, particularly the in-depth analysis of highly cited articles and keywords, clearly reveals that research on psychotherapy dropout places significant emphasis on specific clinical populations and mental disorders. These areas not only constitute research hotspots but may also signify future research frontiers. Among these, PTSD is especially prominent. It not only forms a dedicated keyword cluster (Cluster 7) but is also corroborated by author collaboration networks focusing on PTSD among veterans. Furthermore, PTSD-related literature holds a significant position among the most highly cited documents in the last five years. This highlights that dropout in this domain, particularly concerning specific groups like military veterans, represents a key focus and challenge in current research. A recent meta-analysis reported a 25.6% dropout rate among U.S. service members and veterans, especially in younger individuals, non-manualized approaches, and individual therapy settings (Penix-Smith et al., 2024). Similarly, eating disorders (ED) represent another core research area, evidenced not only by a specific keyword cluster (Cluster 6) but also reflected in the high rankings of influential journals publishing related research. Eating disorders are typically associated with high dropout rates (Linardon et al., 2018; Mahon, 2000), and the academic community has continuously explored dropout mechanisms within this population (e.g., the influence of factors like impulsivity and low self-directedness (Fassino et al., 2009) and intervention strategies (e.g., motivational enhancement (Brewin et al., 2016). Substance use disorder (SUD) likewise emerges as a significant research focus revealed by the bibliometric analysis. Keyword clustering highlighted attention towards the SUD population, particularly female patients (Cluster 4), and its status as a persistent burst term further confirms the enduring research intensity in this area. Considering that SUD is often associated with high relapse risks, treatment dropout may serve as a critical predictor of relapse (Lappan et al., 2019), making the in-depth understanding and intervention of dropout among the SUD population of substantial clinical importance. Furthermore, the results of the keyword cluster analysis in this study also corroborate the field's sustained attention towards other specific populations and disorders: research on schizophrenia and related psychotic disorders constitutes a distinct focus (Cluster 1); explorations of dropout issues among patients with depression, anxiety disorders, and personality disorders are centrally reflected (Cluster 2); and the treatment adherence and dropout problems of adolescents, particularly those with borderline personality features, have also received specialized attention (Cluster 3). Overall, this study objectively delineates the primary landscape of psychotherapy dropout research using bibliometric indicators. The emergence of these hotspots likely stems from their high prevalence in clinical practice, the complexity of treatment, and the severe consequences associated with dropout. This suggests a future need for more personalized dropout risk assessment and intervention research tailored to the characteristics of different populations and disorders.

In addition to focusing on specific populations and disorders, the results of this bibliometric analysis also reveal the academic community's sustained attention to the relationship between psychotherapy approaches and dropout. Cognitive behavioral therapy (CBT) holds a core position in research within this field. This is not only reflected by its appearance as a theme in keyword clusters (Cluster 5) but also evidenced in highly cited meta-analyses on CBT dropout (e.g., Fernandez et al., 2015) and in research utilizing advanced techniques like machine learning to predict CBT dropout (Bennemann et al., 2022; Duhne et al., 2022). Data from one meta-analysis more directly illustrates the high concentration of research focus: among studies examining the relationship between different treatment orientations and dropout, the number of studies on CBT ($k=439$) far exceeds those on other orientations such as psychodynamic ($k=69$), supportive ($k=55$), integrative ($k=47$), and solution-focused therapies ($k=12$) (Swift & Greenberg, 2012). This clearly indicates that, given CBT's widespread application, its associated dropout issues and prediction

mechanisms are a primary research focus in this domain. Concurrently, treatment methods targeting specific disorders also receive considerable attention; for instance, prolonged exposure, highlighted by keyword clustering (Cluster 7) in PTSD research, serves as a representative example. In summary, the analysis results show that while dropout issues associated with specific therapies (such as CBT and trauma-focused therapies) have received considerable attention, further research is still needed to explore how to optimize specific treatment techniques and processes to reduce dropout risk, and to compare the impact of different therapies on dropout rates across diverse populations, thereby providing more refined guidance for clinical practice.

This study's bibliometric analysis further reveals that psychotherapy dropout is a complex phenomenon influenced by multiple factors, encompassing variables at the client, therapist, relationship, and even systemic levels (Barrett et al., 2008; Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993). Among the numerous factors investigated, the core importance of the therapeutic alliance is significantly corroborated by our findings. Keyword cluster analysis included "therapeutic alliance" within a key thematic cluster (Cluster 2), and the highly cited literature identified in this study also contains meta-analyses specifically examining the relationship between alliance and dropout. Such meta-analytic work confirms a moderate association between weaker therapeutic alliances and higher dropout risk (Sharf et al., 2010). In contrast, research on certain static variables (pre-treatment) (e.g., demographic characteristics, some baseline symptoms) often yields contradictory results (Armbruster & Kazdin, 1994; Hatchett & Park, 2003; Stratton et al., 2020; Warnick et al., 2011), making it difficult to draw stable, generalizable conclusions from these factors alone. Conversely, dynamic variables (during treatment), particularly the therapeutic alliance, along with treatment motivation and expectations (as suggested by keyword Clusters 2 and 6), demonstrate more stable and consistent predictive power (Mistier et al., 2016; Sasdelli et al., 2018; Sharf et al., 2010). Notably, our bibliometric analysis, especially through keyword analysis (Cluster 5) and recent citation patterns, captures a significant emerging trend: the application of advanced predictive methods, such as machine learning, to integrate multiple influencing factors. "Machine learning" as a persistent burst term, alongside the emergence of related highly cited studies (Bennemann et al., 2022; Duhne et al., 2022), indicates that researchers are actively exploring how algorithms can integrate multiple predictors from different levels (e.g., education level, age, specific questionnaire scores) to more accurately identify individuals at high risk of dropout. This foreshadows future research directions that require not only continued refinement in exploring various influencing factors and their complex interactions but also a focused effort on translating these integrated predictive models—especially those based on machine learning—into clinically applicable tools, thereby aiding clinical decision-making and advancing towards more personalized dropout risk management.

Concurrent with the in-depth exploration of factors influencing dropout, this study also confirms the academic community's significant emphasis on developing and evaluating dropout reduction strategies. This is evidenced by the analysis of highly cited literature, wherein reviews or meta-analyses systematically summarizing dropout causes and coping strategies have garnered considerable citation impact, indicating the significant reference value of these strategies within the field (Ogrodniczuk et al., 2005; Reis & Brown, 1999; Swift & Greenberg, 2012). Comprehensively, the widely discussed reduction strategies currently revolve around several key areas: First is pre-therapy preparation, which utilizes methods like role induction or experiential pretraining to help patients understand the treatment process, clarify unrealistic expectations, reduce anxiety, and thereby enhance their engagement and adherence (Reis & Brown, 2006; Strassle et al., 2011). Second is motivation enhancement, involving interventions before or early in treatment that employ specific techniques (such as motivational interviewing) to increase patients' willingness to participate and persist in therapy (Jankowsky et al., 2024; Warren et al., 2024). Third, closely related to the previously discussed influencing factors, is the facilitation and maintenance of the therapeutic alliance. Given the core predictive role of the therapeutic alliance in dropout, developing a strong early alliance, continuously monitoring its quality, and promptly addressing ruptures are crucial strategies (Murphy et al., 2022; Steuwe et al., 2023). Furthermore, other noted strategies include respecting clients' treatment preferences (Swift et al., 2018) and utilizing Routine Outcome Monitoring (ROM) and feedback to track progress and adjust treatment accordingly (Barkham et al., 2023). The level of attention these strategies receive is indirectly reflected in this study by the high citation impact of related thematic literature and the prominence of keywords such as "therapeutic alliance" and "motivation" in cluster analysis, suggesting a general consensus within the research community on addressing dropout from these perspectives. However, despite the multitude of strategies, future research must increasingly focus on rigorously evaluating their effectiveness in diverse clinical populations, different cultural contexts, and real-world treatment settings. Additionally, exploration is needed into how these strategies can be applied more personally, based on individual differences and specific situations, to maximally enhance treatment continuation and outcomes.

Synthesizing the findings of this bibliometric analysis, particularly the burst term analysis and the evolutionary

paths of recent literature, several emerging trends in psychotherapy dropout research can be identified, pointing towards future research directions. The most significant emerging trend is undoubtedly the application of advanced data analysis methods such as machine learning. This study found "machine learning" to be the only persistent high-frequency burst term in recent years; concurrently, research utilizing machine learning to integrate multiple factors for dropout prediction has become a focus of highly cited recent literature (Bennemann et al., 2022; Duhne et al., 2022). This strongly suggests that leveraging big data and complex algorithms to understand and predict dropout will be a major frontier for future research, with its core potential lying in integrating complex predictors from various levels. Meanwhile, burst term analysis also reveals sustained or emerging academic focus on specific issues, such as the enduring research interest in dropout related to substance use disorder (SUD), and the recent appearance of terms like "reliable change index" and "early intervention in psychosis". These signals derived from our data analysis may represent subfields or methodological focuses requiring further exploration. Based on these trends revealed by bibliometric analysis and the hotspots discussed earlier, the future research agenda should emphasize several aspects: First, continuous efforts towards refining and standardizing the operational definition of dropout are needed. The high heterogeneity observed across studies in our analysis, along with the recurring emphasis in prior literature that different definitions can lead to contradictory results (Hatchett & Park, 2003; Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993; Xiao et al., 2023), underscores the urgency and challenge of clarifying this fundamental concept. Second, while utilizing methods like machine learning to integrate multilevel influencing factors, future work should focus on developing and validating more precise predictive models applicable in real-world clinical settings, emphasizing model interpretability and clinical utility. Third, attention should be paid to balancing and integrating quantitative and qualitative research. Current research is predominantly quantitative; however, solely relying on quantitative data is insufficient for a deep understanding of patients' subjective experiences and the complex dynamics of dropout, necessitating increased qualitative research. Fourth, there is an urgent need to conduct more effectiveness studies in real-world settings to examine the actual effectiveness and generalizability of factors or intervention strategies proven efficacious under idealized research conditions within routine clinical practice. Finally, future research should strengthen cross-cultural perspectives and international collaboration, paying particular attention to dropout phenomena and interventions in non-WEIRD (Western, Educated, Industrialized, Rich, Democratic) contexts, to overcome potential biases in existing research and enhance the generalizability and cultural sensitivity of findings. Proposing these future directions aims to propel the field towards research that is more in-depth, practical, balanced, and inclusive.

Strengths and limitations

This study has several notable strengths. First, to our knowledge, it is the first to apply bibliometric methods to systematically analyze the literature on psychotherapy dropout, offering a unique, data-driven perspective that complements traditional narrative reviews. By employing quantitative techniques for performance analysis and science mapping, this study provides an objective overview of the publication trajectory, influential contributors (authors, institutions, countries, journals), collaboration networks, thematic research hotspots, and emerging frontiers in the field. This structured mapping helps to uncover patterns and knowledge structures that might be overlooked in qualitative summaries, thereby offering valuable references for researchers navigating this complex domain. Second, the rigorous methodology, including the use of specialized software for thorough data cleaning procedures, enhances the reliability and accuracy of our findings, reducing potential errors and biases that may arise from raw bibliometric data.

However, there are several limitations to this study. First, the data source used—exclusively the Web of Science Core Collection—limits the scope of the literature included, as relevant publications from other databases were excluded. Second, the analysis was restricted to English-language literature, which may introduce language and publication biases and affect the generalizability of the results. Additionally, while we aimed to balance the comprehensiveness and precision of our search strategy, some relevant studies may have been missed, and some unrelated studies may have been included, potentially influencing the outcomes. Finally, while this review offers a valuable summary of the current state of research on psychotherapy dropout, it does not synthesize data from primary studies. Future meta-analyses are needed to aggregate and analyze the dropout data more comprehensively across studies.

Clinical implications

This study maps the research landscape of the psychotherapy dropout field using bibliometric methods. Although it does not directly evaluate intervention effectiveness, the revealed literature structure, hotspots, and trends offer important indirect guidance for clinical practice. First, the high concentration of research focus on specific clinical populations (such as patients with PTSD, eating disorders, or substance use disorders) suggests that clinicians should

maintain heightened vigilance when working with these groups, proactively assessing and managing dropout risk. Second, the persistent emphasis in the literature on the core status of the therapeutic alliance and its strong association with dropout reaffirms the paramount importance in clinical practice of prioritizing the establishment and maintenance of a strong therapeutic relationship; this is not only fundamental to treatment success but also a key intervention point for preventing premature dropout. Furthermore, emerging trends revealed by this study, particularly the application of machine learning in predicting dropout, although perhaps not yet widely translated into clinical tools, foreshadow the potential for future personalized risk assessment; currently, clinicians should focus on known risk factors (such as patient motivation and expectations) combined with clinical judgment for assessment. Additionally, dropout reduction strategies repeatedly discussed in the literature, such as pre-therapy preparation, motivational enhancement techniques, and respecting patient preferences, provide intervention ideas that clinicians can directly reference and apply. Finally, recognizing the current predominance of quantitative research highlighted by this analysis reminds clinicians of the need in practice to look beyond purely quantitative assessments, integrating qualitative observation and communication to more comprehensively understand clients' individual experiences and potential underlying reasons for dropout. In conclusion, understanding the macro-level landscape and focal points of psychotherapy dropout research revealed by this study can help clinicians anticipate potential challenges and adopt more targeted preventive measures to improve treatment adherence and outcomes.

Conclusion

This study, employing bibliometric methods for the first time, systematically maps the knowledge landscape and developmental trajectory of psychotherapy dropout research from 1961 to 2024. The analysis reveals a steady growth trend in research output within the field, characterized by a research landscape dominated by a few countries and institutions, primarily the United States, with specific scholars (e.g., Swift J.K.) and journals (e.g., Psychotherapy) emerging as core contributors. More importantly, through in-depth analysis of literature content and keywords, this study identifies key research hotspots centered on dropout issues within specific clinical populations (especially patients with PTSD, eating disorders, and substance use disorders), the critical role of the therapeutic alliance, and strategies for dropout reduction (such as pre-therapy preparation and motivation enhancement). Concurrently, the research highlights emerging trends in technological application, particularly the potential of machine learning in dropout prediction. This study not only objectively presents the structural characteristics and evolution of the field but also, based on these findings, outlines a critical agenda for future research concerning operational definitions, integration of influencing factors, balancing research methodologies (quantitative and qualitative), validation through real-world effectiveness studies, and cross-cultural expansion. In summary, this bibliometric analysis provides a comprehensive, data-driven macro-perspective for understanding the complex phenomenon of psychotherapy dropout. Its results can serve as a valuable reference for future researchers to grasp field dynamics and focus on frontier issues, while also enhancing clinicians' awareness of dropout risks and intervention strategies.

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Data availability All data generated or analysed during this study are included in this published article and its supplementary materials.

Declarations

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