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Analysis and prospect of clinical psychology based on topic models: hot research topics and scientific trends in the latest decades

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Analysis and prospect of clinical psychology based on topic models: hot research topics and scientific trends in the latest decades

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ABSTRACT

The popularity of research topics in clinical psychology has always been changing over time. In this study, we use Latent Dirichlet Allocation (LDA), a well-established statistical modeling approach in machine learning, to extract hot research topics in published review articles in clinical psychology. In Study 1, we use LDA to extract existing topics between 1981 to 2018 from the review articles published on three premium journals in clinical psychology. Results provide stable information about all topics and their proportions. In Study 2, we use a dynamic variant of LDA to identify the development of hot topics from 2007 to 2018. Results show that *meta-analysis, psychotherapy, professional development*, and *depression* constantly stay as hot topics all over the 12 years. We also find that *behavior intervention* has a clear rising trend since 2007. Our results provide a comprehensive summary of the popularity of research topics in clinical psychology in the last couple of years, and the results here can help clinical researchers form a structured view of past research and plan future research directions.

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Clinical psychology; research trends; topic models; LDA Latent Dirichlet Allocation

Background

Hot research topics have been changing all over the time. Identifying hot topics can help researchers understand research trends in the field and thus assist to form specific research plans and target the core questions in a certain field. Traditionally, summarizing the hot research topics in certain area relies on subjective judgments, which may be biased by personal preferences. This is usually done by leading scientists who have extensive research experiences in a certain field, and as such, their reviews and opinions are reliable. For a young researcher who just enters a field and lacks research experience, understanding research trends is particularly difficult as it is infeasible to manually browse thousands of studies. As such, an object and efficient method is needed to summarize research topics and analyze their dynamic evolution from a large amount of literature.

Topic modeling is an approach widely used in computational linguistics and provides a means for analyzing topics from a large archive of literature (Griffiths et al., 2007).

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Topic models are useful in tasks such as information retrieval, classification, and corpus exploration, and provide a computational solution for managing, organizing, and annotating large archives of texts (Steyvers & Griffiths, 2007). Latent Dirichlet Allocation (LDA) models are the simplest and the most widely used topic models for retrieving latent information from unstructured data, such as textual data. The LDA model is a three-level hierarchical Bayesian model. In the model, each item of a collection is modeled as a finite mixture over an underlying set of topics, and each topic is modeled as an infinite mixture over an underlying set of topic probabilities (Blei et al., 2003). Particularly, it is acknowledged that 'it has similarities with factor analysis and cluster analysis and it identifies underlying clusters of words with semantic similarities (i.e. the "topics")' (D. C. Atkins et al., 2012). LDA models usually extract a set of fixed topics from a chunk of literature without considering the publishing time of the literature. They, therefore, cannot reveal how the structure of sematic topics changes over time. Recently, LDA models are revised into dynamic formats so as to reveal how the popularity of topics evolves over time. A dynamic model considers the publishing order of documents and gives a richer posterior topical structure than static models (Blei & Lafferty, 2006; Steyvers & Griffiths, 2007). In this study, we will use both LDA and its dynamic variant.

Over the latest decades, topic models have already been applied in different domains of psychology. On one hand, researchers use topic models to analyze documents in psychotherapy sessions, clinical interviews, and the contents of patient-related daily talks. In these scenarios, large amounts of linguistic data are generated and often cannot be manually categorized (D. C. Atkins et al., 2012; Carron-Arthur et al., 2016; Howes et al., 2013; Imel et al., 2015). On the other hand, topic models have also been used in analyzing psychological literature. One study retrieved 3104 abstracts from the journal *Cognition* and found several intriguing trends: the rising popularity of moral cognition, eye-tracking methods, and action, the diminishing popularity of sentence processing, and the unchanged popularity of development (Cohen Priva & Austerweil, 2015). Another study analyzed 17723 abstracts related to substance use and depression in the adolescent. They identified brain research as a significantly hot topic in literature (Wang et al., 2016). In 2017, a study used topic modeling to analyze articles published from 1963 to 2015 in *the Journal of Counseling Psychology*. They found that the popularity of the topics related to the counseling process and outcome diminished recently, and the topics related to multiculturalism and diversity show increasing trends (Oh et al., 2017). Therefore, topic modeling is a useful tool to summarize existing hot research topics and predict research trends in the future.

Hot topics are thought to reflect key issues in the field, like therapies, depression and suicide, emotional and behavioral disorders. As aforementioned, the existing application of topic models has been mostly confined in cognitive psychology and counseling psychology. Little research has been conducted in clinical psychology. Therefore, the present research attempts to fill the gap and analyze the literature in the field of clinical psychology.

This study differs from previous studies in two ways. First, we choose literature reviews instead of research articles or reports. Compared with a typical research article, a review article usually targets a representative topic that can better reflect the researcher's interests at that time. Second, to ensure the quality of the reviews, we select three journals with the highest impact factors in the area of clinical psychology according to both Web of Science and Scopus. Specifically, we select three leading journals in clinical psychology – Annual Review of Clinical Psychology, Clinical Psychology Review, and Health Psychology Review. Third, we are interested in not only summarizing the overall research topics in the last couple of decades but also the dynamics changes of topic structures. These changes might provide key insights into the evolution of clinical psychology. To do so, we first use the conventional LDA to analyze all reviews published from 1981 to 2018 to summarize all topics, especially most mentioned topics in the past. Second, we use the dynamic variant of LDA to analyze the reviews from 2007 to 2018 to identify the development of hot research topics in the last 12 years.

Methods and materials

Materials

In Study 1, we retrieved all the titles and abstracts of the review papers from the Annual Review of Clinical Psychology (impact factor 13.278), Clinical Psychology Review (impact factor 9.577) and Health Psychology Review (impact factor 8.597) published from 1981 to 2018. We obtained 285, 1904, and 161 review articles from the three journals, respectively. In Study 2, we retrieved 1301 titles and abstracts of review papers from 2007 to 2018 to balance the sample size (i.e. the number of articles) in each journal.

Preprocessing

The preprocessing steps are as follows: First, we removed punctuations, transformed all letters into lowercase, and merged consecutive blanks to clean up all titles and abstracts. Second, for each row of an abstract, we then removed line breaks, and extracted morphemes, single-character words, English function words, and lemmatizing words. We used a stop-word list in this step. Third, we computed word frequencies and removed the words appearing less than five times. Lastly, we generated a dictionary and transformed the words into a corpus using the dictionary. These preprocessing steps were performed using Natural Language Toolkit (NLTK) (Bird et al., 2009).

Topic modeling

We used Genism Package in Python for topic modeling (Rehurek & Sojka, 2010).

In Study 1, we used LDA to model all 2350 reviews from the three journals. We trained several topic models with different numbers of topics (between 5 and 200) using at most 5000 iterations. The entire corpus had been traversed 20 times to ensure model convergence. The hyperparameters, α and η, were directly learned from the data, which means that it was set to learn the asymmetric prior from the corpus. The α refers to a-prior belief for each topics' probability, and the η means a-prior belief on word probability (Rehurek & Sojka, 2010). To choose the optimal topic number, we considered several factors including sample size, coherence, and manual evaluation. We selected the model with 20 topics as the best model.

In Study 2, we used a dynamic variant of LDA because it considers the publishing time of a document. To balance the number of articles across the three journals, we only selected review papers from 2007 to 2018 and obtained a total of 1301 samples. The selected review papers were chunked every 3 years. Considering sample size, operation time, and interpretability, we then trained topic models with a different number of topics (between 10 and 60) using at most 5000 iterations for each pool size. The entire corpus has been traversed 30 times to ensure model convergence. The hyperparameters, α and η, were learned from the data. We then obtained the proportions of all topics every year.

Evaluation and visualization

The topics inferred through the conventional LDA model are not always interpretable. We calculated c_v coherence, an index of topic coherence offered by Gensim to evaluate the trained models. Topic coherence indicates the degree of interpretability (Chang et al., 2009; Röder et al., 2015) and as a result, can help model selection.

We used LDAvis, a visualizing tool for topic models, to aid interpretations of the topics. The LDAvis provides a global view of extracted topics and how they differ from each other, and allows for a deeper inspection of their representative words (Sievert & Shirley, 2014). LDAvis offers two indexes: saliency and relevancy. Saliency can be used to select the words in visualization, and as a seriation method to highlight differences between topics (Chuang et al., 2012). Relevancy can be used to rank words based on relevancy within topics (Sievert & Shirley, 2014). Moreover, LDAvis can alter the rankings of words to aid topic interpretation. In sum, LDAvis provides several useful utility functions that can help interpret trained models.

Results

Study 1: all topics in clinical psychology during 1981–2018

We selected the model with 20 topics as the best model (see details in Evaluation and Visualization in Methods). All 20 topics and their most relevant words are presented in Table 1. Besides, the proportions of top-10 topics are presented in Figure 1.

Here we denote the top-10 topics from high to low ranks as T0 to T9. We found that T0 pertains to theories and models of cognitive mechanisms in social interactions and takes the largest portion (11.74%) of the whole topic pool. T1 (8.27%) is about the methods for evidence-based treatments, containing words related to both pharmacological and psychological treatments. T2 (7.94%) is related to meta-analyses for assessing therapeutic effects. T3 (6.92%) is about posttraumatic disorders, and T4 (6.22%) is about suicide.

T5, T6, T7, and T8 take a similar proportion (from 5.67% to 5.62%). They are related to counseling and psychotherapy, family, the diagnosis and classifications of mental disorders, sexual abuse, respectively. T9 (4.76%) is about substance abuse and addiction. The topics ranking from 11 to 20 take a total of 31.55% of the whole topic pool.

Study 2: evolution of hot topics in clinical psychology during 2007–2018

In Study 1, we have identified the most extensively mentioned topics in the three leading journals. However, Study 1 only summarizes the content of all topics all over the past (i.e. 1981 to 2018) and cannot reveal how the popularity of these topics evolves over time. We next turned to identify the temporal evolution of these hot topics. Note

Table 1. Twenty topics and their relevant words in Study 1.

T0: theory	Social; model; theory; attachment; process; theoretical; concept; cognition; interpersonal; framework
T1: treatment methods	Treatment; self-help; evidence-based; pharmacological; dissemination; biofeedback; internet; management; practice; medication
T2: meta-analysis	Size; effect; meta-analysis; dropout; study; hedge; tau; small; post-treatment; follow-up
T3: post traumatic disorders	ptsd; trauma; emotion; bipolar; posttraumatic; stress; traumatic; nssi; emotional; dysregulation
T4: suicide	Suicide; hiv; suicidal; suicidality; ideation; sad; mbct; depressive; depression; search
T5: counseling and psychotherapy	Therapist; alliance; client; cam; African; metaphor; news; opiate; psychotherapy; late-life
T6: family	Child; parent; parental; family; caregiver; mother; father; maternal; offspring; adjustment
T7: diagnostic and classification	Diagnostic; personality; validity; dsm-5; edition; classification; manual; statistical; reliability; dsm
T8: sexual abuse	Sexual; sex; offender; abuse; adhd; adulthood; cd; childhood; male; rape
T9: substance abuse and addiction	Substance; bpd; relapse; genetic; sud; hoard; gene; ae; dementia; antibiotic
T10 obesity	Intervention; obesity; loss; weight; grief; kg; randomize; suicide-related; incentive; spiritual
T11 attentional bias	Attentional; bias; fear; anxious; phobia; stimulus; threat; judgment; recall; pain
T12 motivational interview	Behavior; mi; intention; health-related; self-control; bcts; representation; physical; prototype; habit
T13 gender-related problems	Woman; violence; partner; marital; men; intimate; pregnancy; childbirth; drinking; gay
T14 health service	Mental; health; service; school; cross-cultural; rumination; sibling; resilience; community; professional
T15 eating disorders	Eat; nervosa; bulimia; binge; bed; irritability; perfectionism; anorexia; food; weight
T16 therapy	cbt; therapy; trial; remission; rcts; psychotherapy; randomize; pharmacotherapy; college; pretreatment
T17 psychopathy	Veteran; psychopathy; military; psychosis; psychotic; delusion; gamble; dream; amnesia; memory
T18 physical condition	Cancer; crave; subjective; breathe; breast; retrain; extinction; anesthetic; screen, withdrawal
T19 sleep-related problems	Sleep; insomnia; narcissism; sleep-specific; abdominal; rheumatoid; arthritis; pain; rap; icd-11

See Appendix B for definitions of abbreviations.

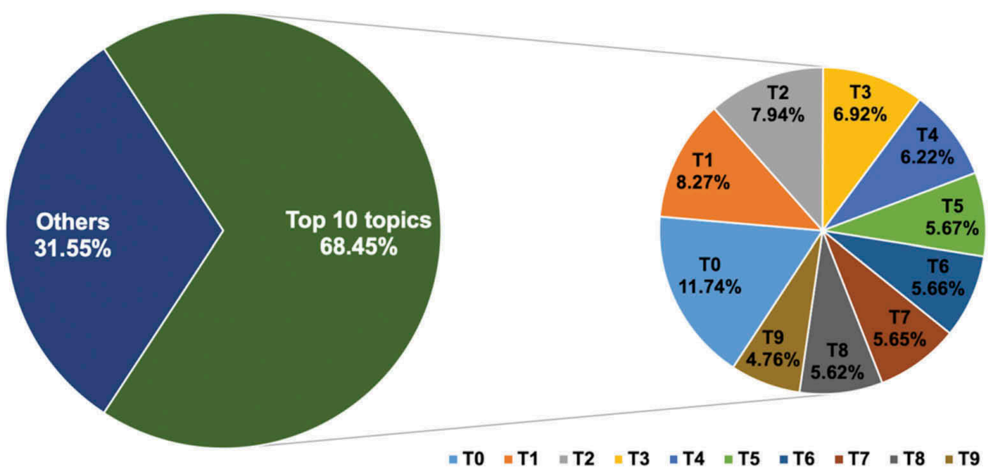

Figure 1. Proportions of generated topics and the top-10 topics from 1981 to 2018. See topic names and relevant works in Table 1.

that the three journals were founded at different times. Annual Review of Clinical Psychology was founded in 2005, Clinical Psychology Review was founded in 1981, and

Health Psychology Review was founded in 2007. The three journals have therefore published different numbers of articles. As such, in Study 2, we set the beginning of the time window as the time when Health Psychology was founded (i.e. 2007). By comparisons of topic coherence, we selected the model with 20 topic numbers as it is easiest to comprehend.

We see some differences between Study 1 and 2. Some topics in Study 1, like obesity, gender, physical condition, sleep, are no longer salient in Study 2. Instead, topics related to disorders, behavioral intervention and prevention, cognitive mechanism, adolescent, emotion have become independent and salient. All 20 topics in Study 2 are offered in Appendix A.

The proportions of the topics in Study 2 change every year; as such, we performed a trend analysis to perform. We define hot topics as the ones that rank top-10 in at least half of the years. A total of 10 hot topics were defined. To characterize the overall increasing or decreasing trends of the topics, we fitted a linear function to their proportions over the years. We also fitted a 3rd-order polynomial function because a linear model cannot reveal the ebb and flow of some topics. Seven of the 10 hot topics had clear changing trends (polynomial function $R^2 > 0.4$) according to Cohen Priva and Austerweil (2015). Here we use the goodness of fit (i.e. R^2) to define the trends as it indicates that our polynomial function captures the considerable amount of variance in the data. The R^2 statistics per se cannot directly indicate the direction of change trends.

The trends of hot topics with their top relevant words are presented in Figures 2–4.

Results showed that *meta-analysis, psychotherapy, professional development*, and *depression/suicide* are the four topics that stably remained hot over the last 12 years. On average, words belonging to these four topics take up 10.06%, 8.82%, 9.00%, and 6.80% of the whole corpus, respectively. Among them, although *meta-analysis* has a relatively lower probability from 2007 to 2011, it peaked in 2012 and remained to be the most frequently mentioned topic since then. The proportion of *professional development* exhibited a sharp decrease from 17.02% in 2007 to 8.50% in 2018. The trends of the other two topics are relatively stable (see Figure 2).

Besides the four hottest topics, *diagnosis, disorder*, and *health service* are another three topics that have been top-10 in nearly all 12 years. *Diagnosis* has a clear decreasing trend (slope = −0.0032). *Disorder* and *health service* are not top-10 topics at the beginning but became hot since then (see details in Figure 3).

Theory, behavior intervention, and *cognitive mechanism* are three topics that were within the top-10 for half of the years. The popularity of *theory* tends to decline in recent years. In contrast, *behavior intervention* significantly rose since 2007 (slope = 0.0084). The popularity of *cognitive mechanism* looks decreasing but overall polynomial fitting is poor ($R^2 < 0.4$).

Finally, among the topics ranking 11–20, five of them (*adolescent, family, prevention, ptsd*, and *sexual*) sometimes entered top-10 and their proportions fluctuate. The proportions of the last five topics never exceed 4% or within top topics before.

Discussion

In this study, we use Latent Dirichlet Allocation (LDA) modeling, the most widely used topic modeling approach, to extract popular research topics in review articles from three leading clinical psychology journals. In Study 1, we identify all hot topics in clinical psychology in the last 30 years. Results show that the topics related to cognitive

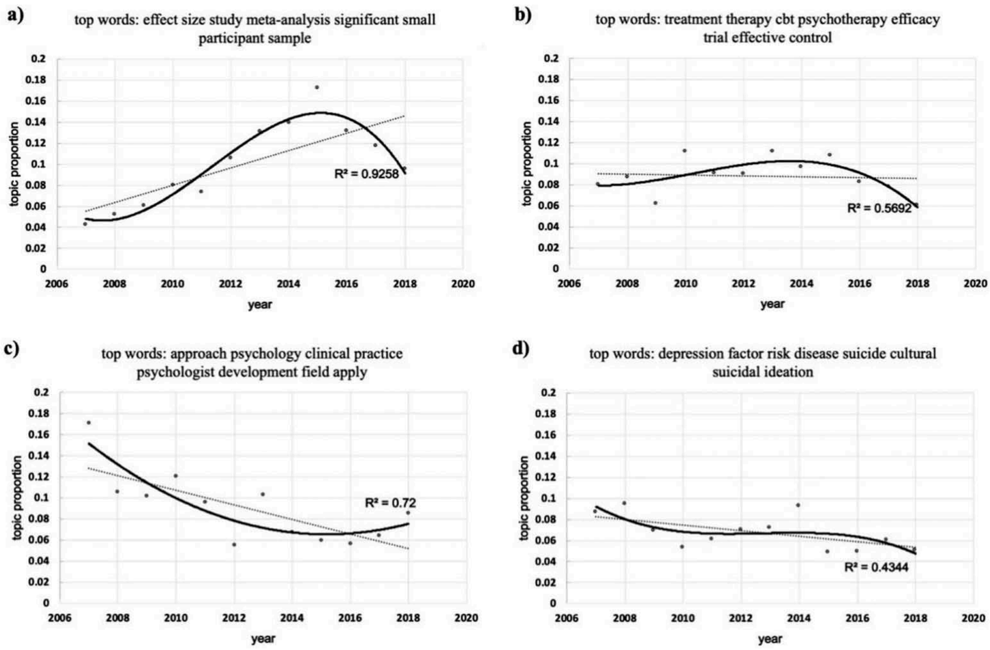

Figure 2. Changing trends of topic proportion for the (a) meta-analysis, (b) psychotherapy, (c) professional development, (d) depression. All these four topics have clear trends ($R^2 > 0.4$) and remain within top-10 topics in every year. The curves are fitted by cubic polynomial functions and the dotted lines are fitted by linear functions using Excel. X-axis indicates year and Y-axis indicates topic proportion. See Appendix B for definitions of abbreviations.

mechanisms in social interactions, evidence-based treatment methods, and meta-analysis of psychotherapies attract most research attention. In Study 2, we use a dynamic version of LDA to investigate the evolution of popular topics in the last 12 years (2007–2018), revealing how clinical psychologists shift research focuses over time.

Despite the different methods and interested time window, we discovered some consistent results across Studies 1 and 2. Most discovered topics are consistent. For example, *theory, meta-analysis, depression/suicide, psychotherapy, diagnosis* etc appeared in both Studies. We also see some differences, topics in Study 1 like obesity, gender, physical condition, sleep are not salient anymore in Study 2. Instead, topics related to disorders, behavioral intervention and prevention, cognitive mechanism, adolescent, emotion have become independent and salient in Study 2, which may indicate the recent focus in clinical psychology. This may be due to the different sampling years we used and reflected the research interests in the different time period.

In sum, these ‘new’ hot topics may help young researchers to form a structure view of contemporary clinical psychology. In particular, these new topics typically accompany the rapid development of science and technology and the drastic change of the socioeconomic status of modern people. For example, many new challenges to mental health emerge in the era of the internet. Understanding these new issues in clinical psychology can guide young researchers to properly organize their research plans.

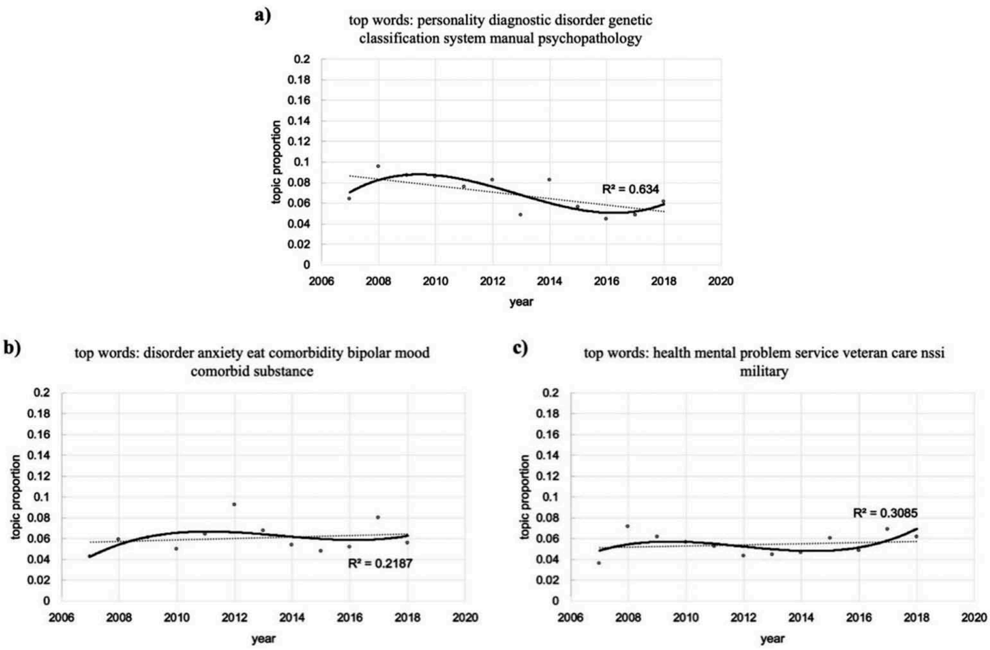

Figure 3. Changing trends of topic proportion for the (a) diagnosis ($R^2 > 0.4$), (b) disorder, (c) health service. Topics (a) are within top-10 topics except for the year of 2016. Topic (b) and (c) have less clear trends ($R^2 < 0.4$), but they are within top-10 topics except for the year of 2007. The curves are fitted by cubic polynomial functions and the dotted lines are fitted by linear functions using Excel. X-axis indicates year and Y-axis indicates topic proportion. See Appendix B for definitions of abbreviations.

Study 2 also aims to examine how hot topics evolve over time. We first identified ten topics that frequently entered top-10 in 12 years. Seven topics out of 10 have been within the top-10 nearly every year. In the seven most popular topics, *meta-analysis* has been the most frequently mentioned topic since 2012. This finding confirmed meta-analysis as an important form of review papers. However, as the popularity of meta-analysis grew substantially in clinical psychology, researchers need to be aware of its limitations such as numerous biases (Delgado-Rodriguez, 2006; Stegmann, 2012; Zwahlen et al., 2008). The proportion of *professional development* decreased, but it still remains a hot topic in the last 12 years. *Psychotherapy* and *depression* were relatively stable and remained hot all over the 12 years. It strongly suggests that depression and suicide have always been core issues. Understanding, preventing depression and suicide have always been of great importance in clinical psychology. Besides, three topics related to diagnosis, disorders, and health services have been also popular over the years. The popularity of *health service* indicates that researchers have increasingly recognized the importance of community-based programs and mental health services in the prevention of mental disorders. It might also be due to the increasingly popular view that community health workers make contributions in reducing the burden of common mental disorders (Asarnow & Miranda, 2014; M. S. Atkins et al., 2017; Marlatt & Witkiewitz, 2010; Singla et al., 2017). Thus, many researchers strive to examining and enhancing the efficacy of community-based mental health services (Biglan & Hinds, 2009). The popularity of *diagnosis* declined since 2013. We speculate that this may be due to The

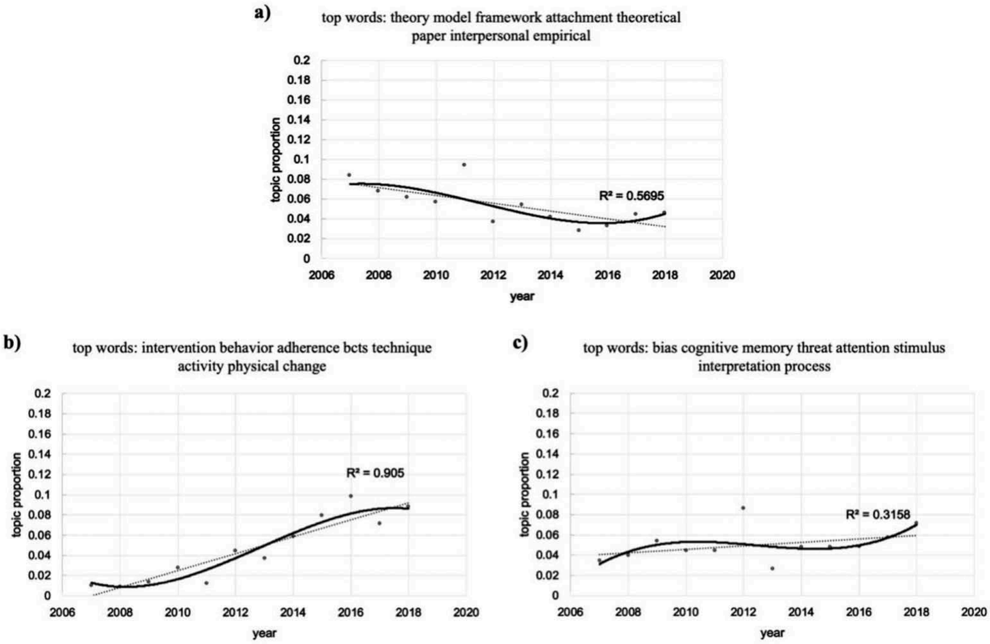

Figure 4. Changing trends of topic proportion for the (a) theory ($R^2 > 0.4$), (b) behavior intervention ($R^2 > 0.4$) and (c) cognitive mechanism. These topics are within the top-10 topics for half of the sampling years. The curves are fitted by cubic polynomial functions and the dotted lines are fitted by linear functions using Excel. X-axis indicates year and Y-axis indicates topic proportion. *See* Appendix B for definitions of abbreviations.

Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) published in 2013. Within these top-10 topics, the popularity of *behavior intervention* exhibited a clear rising trend. We speculate that this is because examining the efficacy of behavioral interventions or psycho-social interventions for both mental and physical illness has increasingly become an essential topic for clinical researches (Dawson & Burner, 2011; DuHamel et al., 1999; Ussher et al., 2009). Also, behavioral techniques in treatment have been applied in many symptoms (Floyd & Moyer, 2010; Murthy & Subodh, 2010). Testing and improving these techniques are in great demand. Recent development of digital devices has also advanced behavior-based techniques for treatment, leading to stronger research interests in enhancing behavioral techniques (Conroy et al., 2014; Lyons et al., 2014; Nikoloudakis et al., 2018). Our findings indicate that clinical psychologists show increasingly greater interests in reviewing and summarizing detailed circumstances for the implementations of behavior-related treatment techniques. However, the trends of some topics like the disorder topic, the health service topic and the cognitive mechanism topic look ambiguous. The overall trends of these topics may be clearer if the time window is lengthened.

There are also some limitations to this study. First, although LDA or DTM can identify topics and their popularity changes using a data-driven approach, they cannot provide direct interpretations and reveal the causes behind these topics and their changing trend. Second, although we tried to only include review articles from the three leading journals, there is still a small chance that the samples are not fully representative. Also, review articles usually reflect research topics that have been extensively studied. As such, also, for review articles, the topic trends may be less salient and change slowly. Review articles might also miss some very new research trends in which not many empirical studies have been conducted. Future studies can broaden the scope of literature, e.g. to analyze most cited articles in clinical psychology. Finally, instead of merely focusing on separate topic meanings, the links between the topics are missing. A more sophisticated analysis approach, such as hierarchical semantic modeling, or network analysis can be used in future studies.

Authors' contributions

S. L. performed the data analysis and wrote the first draft of this manuscript. T. K. contributed to the data analysis. R-Y. Z. contributed to the writing of this manuscript. T. K. supervised this study. All authors read and approved the final manuscript.

Availability of Data and Materials

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Disclosure Statement

The authors declare no competing interests.

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Appendices

Appendix A

Table A1. Twenty topics and their relevant words in Study 2.

Topic	Relevant words
Meta-analysis	Effect; size; study; meta-analysis; significant; small; participant; sample
Psychotherapy	Treatment; therapy; cbt; psychotherapy; efficacy; trial; effective; control
Professional development	Approach; psychology; clinical; practice; psychologist; development; field; apply
Diagnosis	Personality; diagnostic; disorder; genetic; classification; system; manual; psychopathology
Depression	Depression; factor; risk; disease; suicide; cultural; suicidal; ideation
Disorder	Disorder; anxiety; eat; comorbidity; bipolar; mood; comorbid; substance
Health services	Health; mental; problem; service; veteran; care; nssi; military
Theory	Theory; model; framework; attachment; theoretical paper; interpersonal; empirical
Behavioral intervention	Intervention; behavior; adherence; bcts; technique; activity; physical; change
Cognitive mechanism	Bias; cognitive; memory; threat; attention; stimulus; interpretation; process
Adolescent	adhd; adolescent; antisocial; behavior; youth; hyperactivity; executive; peer
Family	Parent; child; family; social; parental; fatigue; father; mother
Prevention	Program; prevention; pain; skill; school; competence; young; intervention
ptsd	ptsd; trauma; stress; posttraumatic; traumatic; sleep; injury; exposure
Sexual problems	Sexual; abuse; partner; offender; couple; sex; woman; intimate
Substance	Alcohol; screen; relapse; use; safety; cancer; drink; consumption
Emotion	Emotion; regulation; reactivity; positive; psychopathy; worry; acceptance; dysregulation
ocd	ocd; symptom; patient; internalize; sibling; grief; schedule; perception
Schizophrenia-related brain impairment	Schizophrenia; deficit; functional; brain; auditory; voice; perceptual; impairment
Phobia	Phobia; anger; instrument; definition; trait; consumer; empathy; compassion

The nature of DTM constrains that the topics are the same across years so that we only present one list of most relevant words. No topic rankings are provided and there is no particular order for these topics because they tend to change every year. See the text for details.

Appendix B.

Table B1. Definitions of abbreviations in all tables and figures.

Abbreviations	Definitions
adhd	Attention deficit hyperactivity disorder
ae	Alcohol expectancies
bcts	Behavior change techniques
bpd	Bipolar disorder
cam	Complementary and alternative medicine
cbt	Cognitive behavior therapy
cd	Conduct disorder
dsm	The Diagnostic and Statistical Manual of Mental Disorders
hiv	Human immunodeficiency virus
icd-11	International Classification of Diseases
mbct	Mindfulness-based cognitive therapy
mi	Motivational interview
nssi	Non-suicidal self-injury
ocd	Obsessive-compulsive disorders
ptsd	Post-traumatic stress disorder
rcts	Randomized controlled trials
sud	Substance use disorder