

Why Research From Lower- and Middle-Income Countries Matters to Evidence-Based Intervention: A State of the Science Review of ACT Research as an Example

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Despite the global nature of psychological issues, an overwhelming majority of research originates from a small segment of the world's population living in high-income

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countries (HICs). This disparity risks distorting our understanding of psychological phenomena by underrepresenting the cultural and contextual diversity of human experience. Research from lower- and middle-income countries (LMIC) is also less frequently cited, both because it is seemingly viewed as a “special case” and because it is less well known due to language differences and biases in indexing algorithms. Acknowledging and actively addressing this imbalance is crucial for a more inclusive, diverse, and effective science of evidence-based intervention. In this state-of-the-science review, we used a machine learning method to identify key topics in LMIC research on Acceptance and Commitment Therapy (ACT), choosing ACT due to the significant body of work from LMICs. We also examined one indication of study quality (study size), and overall citations. Research in LMICs was often nonindexed, leading to lower citations, but study size could not explain a lack of indexing. Many objectively identified topics in ACT research became invisible when LMIC research was ignored. Specific countries exhibited

potentially important differences in the topics. We conclude that strong and affirmative actions are needed by scientific associations and others to ensure that research from LMICs is conducted, known, indexed, and used by CBT researchers and others interested in evidence-based intervention science.

Keywords: lower- and middle-income countries; acceptance and commitment therapy; topic modeling; inequity; journal indexing

THE RELATIONSHIP of science and practice between higher-income countries (HICs) and lower- and middle-income countries (LMICs; [World Bank, 2024](#)) is complex and influenced by economic disparities and intercultural communication. Much of the attention of the HIC scientific community toward issues of culture and diversity in evidence-based therapy has been on barriers to dissemination, health disparities, or the practical need for cultural modifications of intervention methods ([Busse & August, 2020](#); [Idrovo, 2024](#); [Plancikova et al., 2021](#)). These are important topics, but they occur in the context of a larger issue that can readily be underemphasized: a worldwide scientific imbalance across cultural and economic divides that profoundly affects the cultural, practical, and empirical dimensions of our current evidence-based care approaches.

In 2010, it was estimated that 96% of the world's psychological research came from 12% of the world's population—those living in so-called WEIRD countries—Western, Educated, Industrialized, Rich, and Democratic ([Henrich et al., 2010](#)). A decade later a similar analysis found similar results ([Thalmayer et al., 2021](#)). The citation of scientific literature is similarly skewed ([Cheek, 2017](#)).

The potential for knowledge distortion produced by this scientific imbalance is enormous. For example, of the 100 most eminent psychologists identified by [Diener et al. \(2014\)](#), fewer than 10% spent a large part of their careers outside the United States. Researchers in the United States published approximately half of all psychology publications in the 15 years before 2010 ([O'Gorman et al., 2012](#)). In a study of the 100 most cited articles in science, not even one had a first author from an LMIC ([Uthman et al., 2013](#)).

Unfortunately, even when there is an attempt to produce and consume more diverse research studies, implicit biases can get in the way of authors and readers alike. For example, studies from the United States are less likely to name their country of origin in their titles as compared to studies from other areas, unless they were focused on racial/eth-

nic/cultural minorities, in which case they were *more* likely ([Cheon et al., 2020](#)). This pattern suggests that research on more diverse populations was perceived by researchers themselves as exceptions to the implicitly assumed generalizability of findings with White Americans. Studies from LMICs, meanwhile, were more prone to include the sample's country in the title, but this practice is associated with fewer citations, implying that such mentions reduce the level of general interest by framing the findings as “special cases” to the assumed generalizability of findings from HIC research ([Kahalon et al., 2022](#)).

As it applies to the science of evidence-based therapy, stifling the voices of LMICs and artificially augmenting the voices of HICs induce potential biasing effects that are difficult to predict or model without extensive data. For example, some issues may be more common in LMIC research than HICs (e.g., war, social order, poverty, immigration, political upheaval, economic sanctions, class differences, and so on), and Western dominance could reduce awareness of or attention to these issues. Intervention ideas drawn from particular religious or wisdom traditions that differ across HICs and LMICs may be augmented or diminished, resulting in needless narrowing or distortion of topics of interest. Some evidence-based methods may be particularly popular in LMICs as compared to HICs, or vice versa, and thus a comparative examination of the impact or prevalence of specific approaches may be hindered by the relative invisibility of LMIC research. The consistency or inconsistency of the impact of particular methods across cultures may be over- or underestimated due to a documented bias against considering or citing LMIC research ([Kahalon et al., 2022](#)). In medical areas, for example, there is evidence that randomized trials in HICs are more likely to be both industry-driven and well-cited but are less likely to target problems in proportion to their social health burden ([Wells et al., 2021](#)).

In an era of easy access to communication systems that extend worldwide, monoculturalism and ethnocentrism are increasingly arbitrary and out of step with reality, regardless of country of origin. However, without an examination of the full range of research available across HICs and LMICs, significant input into these issues is diminished. If some methods have a similar impact across cultures, that fact will be less known; if some have a more differentiated impact, that too will be less visible.

Infrastructural challenges significantly complicate the resolution of this issue. Governmental or

large commercial entities (e.g., Elsevier/Web of Science; Clarivate/Scopus; PubMed) maintain the indexing systems that orient researchers to scientific information, but they are heavily slanted against LMICs. Journals can take many years to receive impact factors, and journals from LMICs are often nonindexed, even for decades on end. Indexed and highly cited open-access journals can be read by LMIC professionals with internet access, but they often charge publication fees that are far beyond the means of LMIC authors, restricting the flow of information (Newton, 2020). Further, publications in English journals are significantly more likely to be both indexed and cited (Di Bitetti & Ferreras, 2017) but this puts an added burden on sometimes already underresourced scientists who are not native English speakers, either to learn a different language even in technical areas, or to be subject to relative invisibility simply due to country of origin. The present paper begins to address these issues by providing a detailed examination of ACT studies in LMICs.

ACT AS A CASE EXAMPLE OF LMIC RESEARCH

The present state-of-the-science review (see Comer, 2024) offers a case example of the possible importance of taking such affirmative steps. We sought to summarize the topics and potential impact of LMIC RCTs on Acceptance and Commitment Therapy or Training (ACT in either case; Hayes et al., 2012). There are many reasons to focus on ACT research for considering how research in LMICs might inform the development of CBT or other evidence-based interventions more generally.

ACT is widely recognized as an evidence-based approach by such bodies as the World Health Organization or the Centers for Disease Control (for a list see https://contextualscience.org/state_of_the_act_evidence), and has for decades been at the forefront of the development of so-called “third-wave” CBT (Hayes, 2004). The rate of research in ACT is quite high, including in LMICs. If randomized controlled trials (RCTs) alone are considered, they exceed 1,000 in number and more than 45% of these have been conducted in LMICs (Hayes & King, in press). For many years, the Association for Contextual Behavioral Science (ACBS) has attempted to list every RCT done on ACT for any problem conducted anywhere in the world (see bit.ly/ACTRCTs). ACBS has chapters throughout the world and in addition to calls for input from members, its staff and developing nations committees have regularly examined databases of research in specific LMICs to find ACT

RCTs. Studies are added regardless of findings. While such a list cannot be said to be comprehensive, the sheer volume of identified LMIC research provides a good starting point for considering the role of LMIC research in CBT.

Further, unlike some forms of CBT that are focused on syndromes or problem areas, ACT has been consciously built upon a process-based approach that relies on a small set of relatively basic processes of change within a single “psychological flexibility” model that can then be applied in a radically transdiagnostic fashion. Hayes and King (in press) found that the first 1,000 ACT RCTs had focused on medical illness (e.g., cancer, diabetes, and multiple sclerosis) and physical impairment 26% of the time, DSM diagnoses (21%), behavioral health (weight loss, exercise, smoking, and other substance use—10%), performance (including academic, workplace, or athletic performance—7%), parents or caregivers (including clinicians—9%), chronic pain (6%), social concerns (4%) and a variety of other less frequent topics. This broad diversity of topics may afford a more sensitive examination of LMIC research than in other, more focused forms of evidence-based intervention such as those that primarily address particular DSM syndromes, especially if interest in these targets vary.

The process-based approach of ACT also in principle might afford more flexibility interculturally. At least in broad strokes, psychological flexibility appears to be central to the impact of all common forms of CBT (Hayes et al., 2022; Salkovskis et al., 2023). In ACT, psychological flexibility processes are cast in ways designed to maximize their ability to be fit to specific clients with specific cultural backgrounds. For example, while an ACT approach embraces the importance of values choices, it does not maintain a list of values to be embraced by clients. Instead, ACT asks clients to fit their experiences and preferences into the values component of the model. These features suggest that a state-of-the-science examination of ACT LMIC research might cast light on how CBT more generally might benefit from paying more attention to LMIC research.

CURRENT STUDY

It is difficult to characterize diverse literatures without bias, so in the primary analysis in the present study, we applied a machine learning approach that objectively identified the topics of research in the RCTs of ACT conducted in LMICs spanning more than a decade. This analysis involved automated text mining of the English abstracts of the relevant RCTs. At the same time,

it seemed important to amplify the voices of LMIC researchers in a more qualitative way. We did so in the present study by describing the exemplar studies of certain key topics of nonindexed LMIC research abstracts. The goal of the quantitative topic modeling and qualitative narratives was to assess the importance of attending to the LMIC clinical and research community and to evaluate some of the barriers to doing so.

Materials and Methods

COLLECTION OF ABSTRACTS

We built a dataset for this study by extracting the citations of ACT RCTs from LMICs reported in Hayes and King (in press) and searching for their abstracts online. Their database comprised the first 1,015 ACT RCTs from the years 1986–2023 that were listed on the website of Association of Contextual Behavioral Science (contextualscience.org) at the time of their data collection. Details of how the database was constructed can be found in Hayes and King (in press) but as it applies to the present topic it included consulting a long list of national or regional databases, and reference lists of meta-analyses that covered non-English articles (ACBS, 2023).

For the purposes of the current study, the primary focus was the 464 RCTs that appeared in journals with their home offices in LMICs. Affiliations of authors were not used to determine country or origin because concurrent use of ORCID or similar identification systems is highly inconsistent in LMICs, and affiliations were not always fully noted, making author by author determinations difficult. For each of the studies, the English abstract and article full text were retrieved (if available). Full text English versions of the paper were available for 27.80% ($n = 129$) of the publications, and thus we focused our analysis on the English abstracts of LMIC articles rather than the full text of the paper, given that English abstracts were available for almost all papers even when the full paper was in non-English language. For a few papers ($n = 16$) the abstract was only available in a non-English language (14 in Chinese and 2 in Arabic). In those cases, the abstract was translated into English using Google Translate. Google Translate can sometimes introduce errors in grammar, vocabulary, idioms and colloquialisms. This issue was largely handled by our innovative analytical approach (explained below) in which text data is tokenized and stemmed, removing grammatical elements such as punctuation. For another 3 papers, the abstract could only be found through a Google Scholar citation page and was

thus truncated. One paper was found to have been retracted, so was omitted from our analyses. For 7 papers, the abstracts could not be found.

Therefore, in the final sample of our study, 457 English abstracts were analyzed to examine the topics in the ACT RCT research landscape in LMICs. The data and sample R code of topic modeling we used in this study can be found in Supplemental Materials. Of the references in our data, 259 had DOIs but only 216 were valid DOIs. Alternative links are provided for the 242 papers with missing or invalid DOIs. The year of publication of the articles ranged from 2011 to 2023. Of the 457 abstracts, 13.79% ($n = 63$) were from publications in indexed journals and 86.21% ($n = 394$) in nonindexed journals. Regarding the target population of the studies, we used the manually coded variable from the dataset of Hayes and King (in press) to create a dichotomous variable of whether the article focused on a DSM defined population: 24.51% ($n = 112$) of the studies in our sample had a DSM focus whereas a majority 75.49% ($n = 345$) did not. The following countries (and number of abstracts) were represented in the data: Iran ($n = 350$), China ($n = 61$), India ($n = 17$), Thailand ($n = 6$), Brazil ($n = 5$), Turkey ($n = 4$), Pakistan ($n = 3$), Egypt ($n = 2$), Indonesia ($n = 2$), Macedonia ($n = 2$), Palestine ($n = 1$), Russia ($n = 1$), Algeria ($n = 1$), Brazil ($n = 5$), Bulgaria ($n = 1$), and Ethiopia ($n = 1$). Despite the dominant categories of Iran (76.59% of the abstracts) and China (13.35%) as sources of publications, we followed best practice of using all available data from all countries, which served our goal of examining the topics in LMICs publications accounting for any country-level variation and other factors like year of publication, indexing of journals, and DSM focus. We examined the effects of these covariates on the prevalence of identified topics in the corpus of the abstracts. We also ran additional topic modeling using a separate subset of the abstracts from Iran to see if there were any unique topics in the abstracts from Iran that might have been missed in the topics identified in our main models using the data from all LMICs.

Supplementary materials, including the data and R code for structural topic modeling used in this study, are available on Open Science Framework: https://osf.io/dtzkx/?view_only=a2f90b2a96bd43a6bcd46e4a62d1c9c1.

Structural Topic Modeling of Abstracts

Structural Topic Modeling (STM) is an unsupervised machine learning method of analyzing text data for examining latent topics (Roberts et al., 2016; Roberts et al., 2019). It assumes that every

document (abstract in our case) is a mixture of topics, and every topic is a mixture of words. Words can overlap across topics and topics can overlap across documents. STM is superior to the commonly known probabilistic topic models, such as Latent Dirichet Allocation (LDA), because it incorporates covariates in the modeling technique such that documents that have similar levels on a covariate tend to have the same topic prevalence and tend to use the topics in the same way, that is, have similar content or rate of word use within a given topic (Roberts et al., 2016). Further technical details of STM can be found in Roberts et al. (2016) and the method's implementation in the R package, *stm* (Roberts et al., 2019).

STM has been shown to produce results that are as good, if not better than, the results obtained using traditional manual thematic analysis techniques (Towler et al., 2023), but it has the advantages of being far more efficient than “human-only” qualitative analysis and producing fully reproducible results, which is often a limitation of traditional qualitative methods (Pokorny et al., 2018). Another advantage of using a fully reproducible, largely automated STM approach is that its results are less likely to be influenced by ideological biases that can influence manual thematic analysis by humans. We tried to minimize such biases further through discussions among co-authors at every stage of the study, who represent diverse cultures and live in different countries including HICs and LMICs.

Following standard procedures (Roberts et al., 2016), preprocessing of the abstracts text data involved tokenizing, removing numbers, punctuation, any extra white space, and stop words using the SMART stopword list, and transforming the corpus to lowercase. Stemming, another normalization technique of natural language processing, was used to lower the inflection in words to their root forms (e.g., “acceptance” can be reduced to the word stem “accept”). Further, words that appeared in less than 5% of the abstracts and those that appeared in more than 95% were dropped to refine the focus on relevant vocabulary and enhance model accuracy.

The preprocessed data consisting of 457 documents (abstracts), 283 terms, and 25,646 tokens were subjected to a series of STM models with the four covariates of year, indexing, DSM focus, and country. We varied the number of topics to extract from 5 to 40 in increments of 5 and compared the following diagnostic properties for each of these models: held-out likelihood (models' ability to predict unseen data), semantic coherence (the topic consistency within a document, with

bigger numbers being better), residual dispersion (variation in topic distribution not explained by the model), and lower bound (a correction to the “bound” for each model to make the scores comparable across models). Higher values of held-out likelihood, semantic coherence, and lower bound, and lower values of residuals indicate better fit, which is summarized in the diagnostic plot of the *stm* package (Roberts et al., 2019).

As shown in Figure S1 in Section 1 of Supplementary Materials, a model with 30 topics appeared to be most “optimal” given its relatively high held-out likelihood, reasonable coherence, lower-bound, and lowest residuals. We also ran sensitivity models of topics around 30 using the increments of 2, which also showed a 30-topic solution to be reasonable. We then ran a final STM model with the same four covariates and selected 30 topics to extract.

STM yields topic proportions for each document. That is, each abstract is represented by the proportion of its words that come from each of the topics. These proportions are depicted in Figure 1, which shows a heatmap of the 457 abstracts by 30 topics matrix of topic proportions. Figure S2 in Section 2 of Supplementary Materials depicts the overall expected topic proportions of the 30 topics across all abstracts.

Results and Discussion

LABELS OF TOPICS

Table S1 in Section 3 in Supplementary Materials provides the top words in each of the topics based on the highest probability of words and the “FREX” criterion, which identifies the most characteristic words in topics by using the harmonic mean of word frequency and exclusivity across topics (Airoldi & Bischof, 2017). It also contains three example abstracts for each topic. Table 1 contains the labels of the topics that we created based on the discussion between all co-authors, who read the top words and sample abstracts for each topic. Based on those discussions, we tentatively deemed some of the topics (indicated by an asterisk * in the labels in Table 1) as meaningful but potentially non-substantive. The latter topics, while relevant to broad ACT categories, appeared non-substantive, not aligning with the study's goal of exploring the substantial topics within the ACT RCTs research landscape in LMICs. For instance, topics such as Observation of Intervention Groups, and ACT Psychotherapy Treatment, while meaningful and fully interpretable, did not provide discriminating information about the sub-

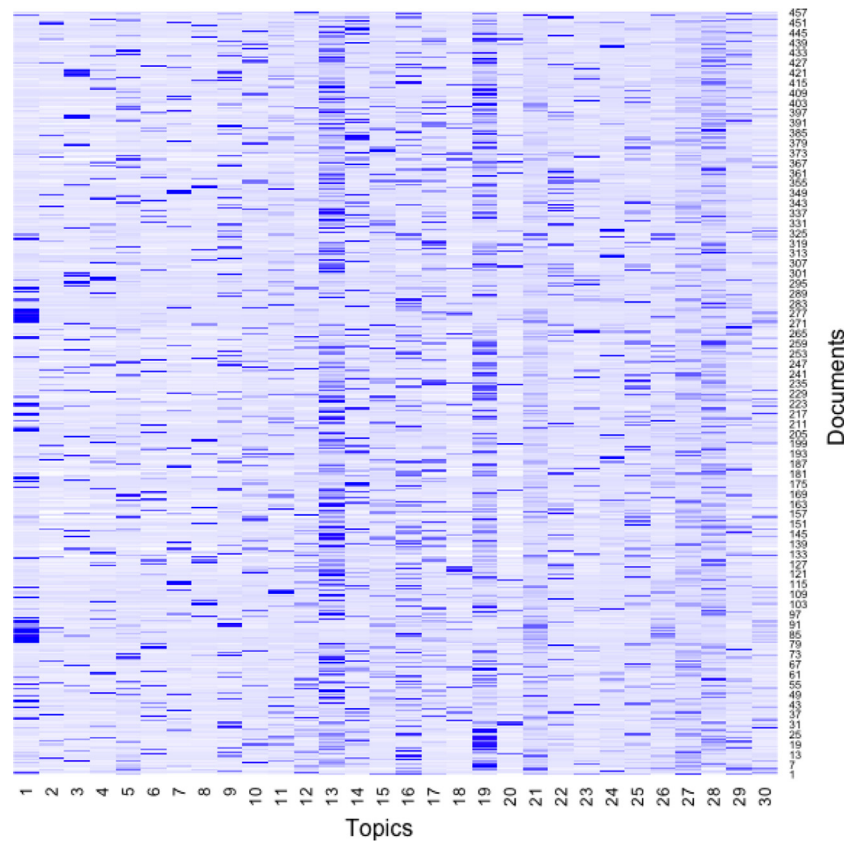


FIGURE 1 A heatmap of the prevalence of all topics across all abstracts.

Table 1
Labels of the 30 Topics From Structured Topic Modeling Analysis

1. *Observation of Intervention Groups	16. Anxiety and Depression
2. Couples Functioning and Satisfaction	17. Quality of Life
3. Mothers of Special Needs Children	18. Cancer
4. Adolescents Mental Health	19. *ACT Compared to Other Therapies
5. Cognitive-Emotion Regulation	20. Resilience and Adjustment
6. Chronic Pain	21. ACT During Rehabilitation
7. Type 2 Diabetes	22. Stress Reduction
8. Bodily Concerns	23. Family Functioning
9. School Students	24. *ACT Counseling
10. Psychological Well-Being	25. Distress of Physical Diseases
11. ACT Mindfulness Training of Non-Clinical Populations	26. Self-Efficacy or Self-Esteem
12. ACT Combination Treatments	27. Relationship Studies
13. Statistics Related Terms Usage	28. *Pre-Post Experimental Design
14. Dynamics of Marital Satisfaction Among Women	29. *ACT Psychotherapy Treatment
15. Physical and Mental Disability	30. *Psychological Flexibility

Note. *Topics that were meaningful but potentially unhelpful in examining the substantive topics of the ACT RCTs research landscape in LMICs. See Section 2 of Supplementary Materials for top words based on highest probability and the FREX criterion, and three example abstracts for each of the 30 topics.

stantive problems for which ACT is used in LMICs. Still, in the interest of complete reporting, we report all results of all analyses conducted on all topics in Supplementary Materials. In the

results reported below, we use the phrases “topic prevalence” and “expected topic proportion” interchangeably; they both mean the proportion of documents devoted to a given topic.

EXPECTED TOPIC PROPORTIONS AS A FUNCTION OF COVARIATES

Section 3 in Supplementary Materials contains the narrative details of all analyses, with figures and tables related to those analyses reported in the subsequent sections of the Supplementary Materials. We report selected results in the main text here for brevity.

Year of Publication

The year of publication had a statistically significant effect on the expected topic proportions for 8 of the 30 topics. As shown in Figure 2, the topics of Adolescents Mental Health, ACT Mindfulness Training in Non-Clinical Populations, ACT Combination Treatments, and Physical and Mental Disability (right panel) seem to have been declin-

ing in popularity over time, whereas the topics of Statistics Related Terms Usage, ACT Compared to Other Therapies, Self-Efficacy or Self-Esteem, and Relationship Studies (left panel) seem to be “hot” topics gaining in popularity in the ACT RCT research landscape in LMIC.

Indexing

The covariate of indexing had a statistically significant association with topic prevalence with six topics shown in Figure 3. For the topics of Resilience and Adjustment, Pre-Post Experimental Design, ACT Psychotherapy Treatment (left panel of Figure 3), the expected topic proportion estimates were significantly higher for nonindexed than indexed sources. Conversely, for the topics of Cancer, Stress Reduction, and Relationship Sta-

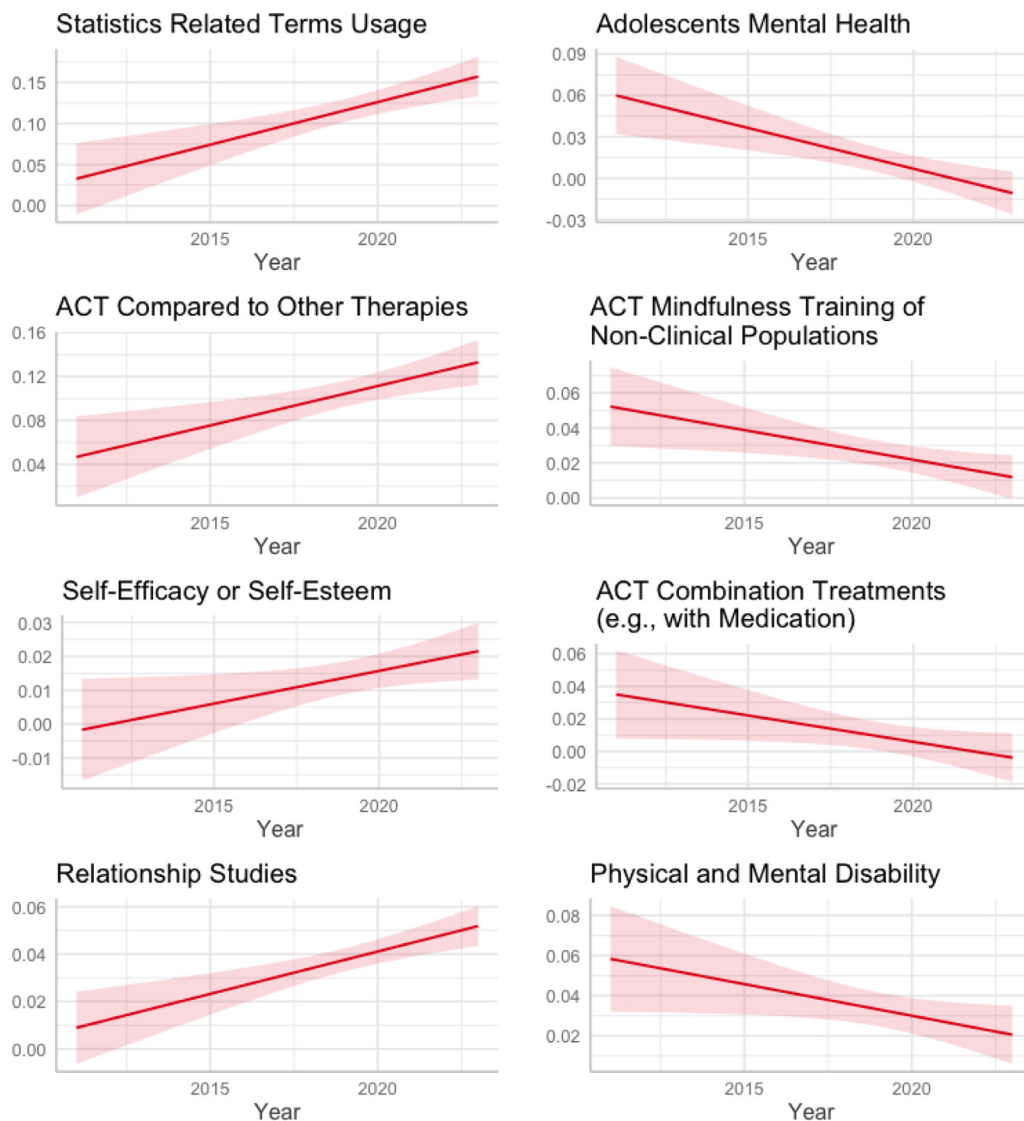


FIGURE 2 Model-based expected topic proportion of the topics as a function of year of publication. Note. Figure S3 in Supplementary Materials contains plots for all topics. The plots for substantive topics that showed a statistically significant effect of year are shown here.

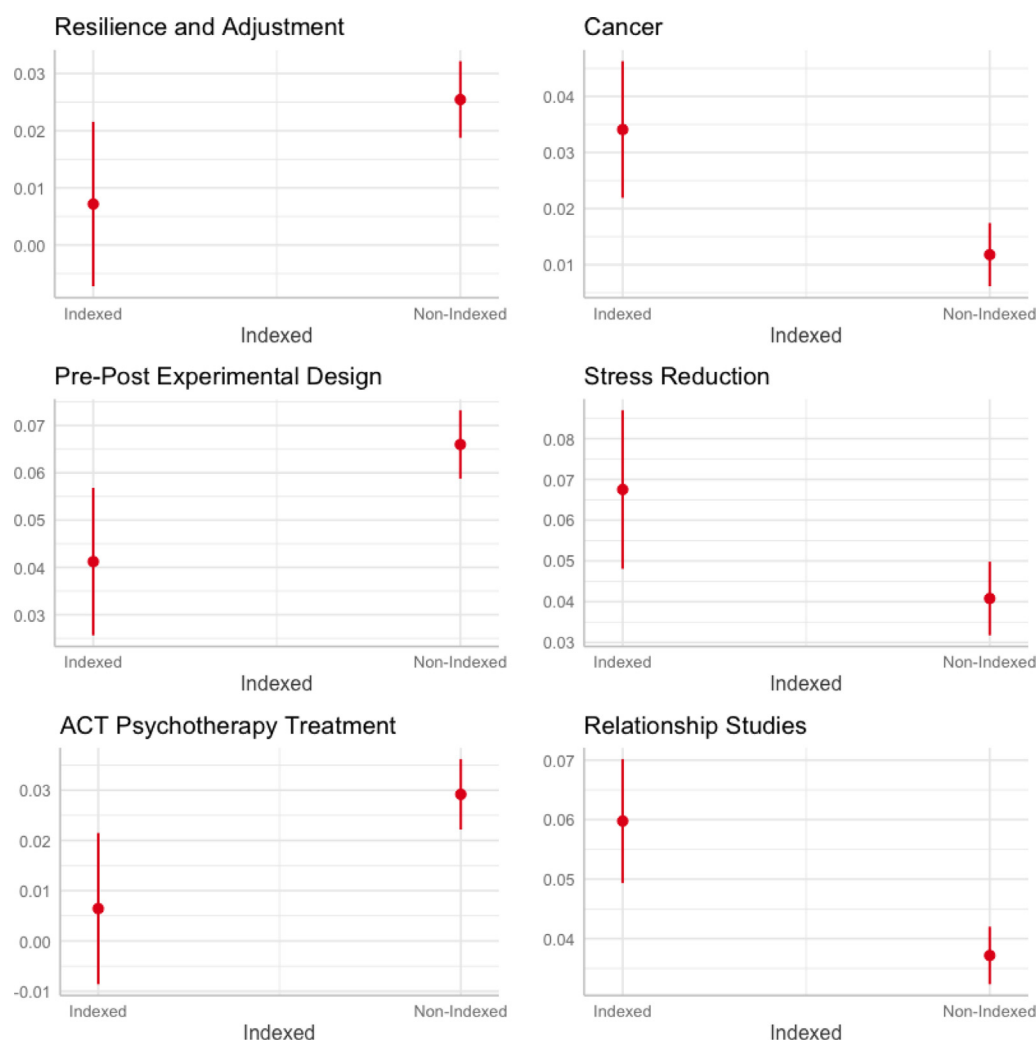


FIGURE 3 Model-based expected topic proportions of topics as a function of indexing of the source of the abstracts. *Note.* Figure S4 in Supplementary Materials contains plots for all topics. The plots for topics that showed a statistically significant effect of indexing are shown here.

tus (right panel of Figure 3), indexed sources, relative to nonindexed ones, showed higher expected topic proportions. For all other topics (Figure S4 in Section 6 of Supplementary materials), the results showed that the prevalence of most topics was reliably different from zero in nonindexed sources, which is not surprising given that a vast majority of the abstracts (86.21%) in our samples were of articles published in nonindexed journals.

In an analysis of the indexed sources alone (Figure S5, Section 7), at least six of the substantive topics, such as Mothers of Special Needs Children, Resilience and Adjustment, and Family Functioning from the full set disappeared in the subset of indexed sources, leaving studies on physical conditions, stress, self-esteem, or relationships primarily. Stated another way, ignoring nonindexed studies would have dramatically changed what

appeared to be important topics of research in LMIC countries, suggesting that even in a body of research that spans several hundred studies if LMIC voices are to be heard with clarity, the professional community will have to overcome the barrier of indexing.

Country

Figure S6 in Section 8 of Supplementary Materials contains the plots for all 30 topics showing the point estimates and 95% CIs of expected topic proportions as a function of the country of publication. We discuss the nuances of the country-level effects in Supplementary Materials (see narrative details in Section 3) and provide a few examples here. For instance, the topic of Adolescents Mental Health was important in India, Bulgaria, Ethiopia, and Indonesia, but the effects for other countries were not reliably different from

zero. Chronic Pain was prevalent in the abstracts from India, China, Brazil, Iran, and Algeria. Expected topic proportions for Type 2 Diabetes were reliably different from zero for Iran, Turkey, and Macedonia.

The point estimates of the topic of School Students were reliably different from zero for India, China, Thailand, Iran, and Egypt, but not other countries. For Psychological Well-Being, the following countries had point estimates of topic proportions that were reliably different from zero: Iran, Palestine, Algeria, and Macedonia. The topic proportion for ACT Mindfulness Training of Non-Clinical Populations was substantially high in the abstract from Russia but was also reliably different from zero for abstracts from India, China, Thailand, and Iran. These findings confirm that although the abstracts from Iran and China were the majority in the sample, the topic proportions in general were not necessarily dominated by those countries. Put differently, our STM solution identified meaningful and substantive topics from the minority sources just as well as the majority ones.

Dynamics of Marital Satisfaction Among Women was prevalent in the abstracts from India, Iran, and Macedonia. This finding again highlights that certain topics are studied in some cultures but not others. It also confirms that our STM model did a reasonable job in identifying the topics that traverse the abstracts in our sample from diverse countries that share a low- or middle-income status but otherwise exhibit socio-political differences.

There were a couple of topics for which there were no reliable country-level differences: Mothers of Special Needs Children and Bodily Concerns. As shown in the plots in Figure S5 in Supplementary Materials, the expected topic proportion of these topics was reliably different from zero for the abstracts from Iran but not the other countries. The 95% CIs of the point estimates of each of these topics overlapped across all countries, hence the differences between countries were not reliable. Not surprisingly, the effect of the abstracts from Iran, the largest category in our sample, for these topics (like most of the other topics) had the narrowest CIs, i.e., the most precise estimate, whereas the CIs of point estimates of many of the other countries were wide due to relatively fewer abstracts from those countries in our sample.

We ran sensitivity tests by running STM on the abstracts from Iran alone. As shown in Figure S7 in Section 9 in Supplementary Materials, a 30-topic solution was the most optimal. Figure S7 also shows that the topics overlapped with the ones we

found in the analysis of the full sample, which is not surprising given that the Iranian abstracts were the majority in our sample. Importantly, no topic was unique in this subset that was missing in the solution based on the full sample.

DSM Focus

Finally, we examined whether or not the article focused on DSM categories predicted topic proportions. See Figure S8 in Section 10 in Supplementary Materials. As might be expected, several DSM-sounding topics—Bodily Concerns, ACT Combination Treatments (e.g., with Medication), Anxiety and Depression, Self-Efficacy or Self-Esteem—had higher topic proportions among abstracts that had a DSM focus. The topic of Adolescents Mental Health also showed higher topic proportions among abstracts that had a DSM focus in large part due to the focus on social anxiety in some of these studies. Several other topics—Couples Functioning and Satisfaction, Chronic Pain, Psychological Well-Being, Resilience and Adjustment, Stress Reduction, and Distress of Physical Diseases—had lower topic prevalence in abstracts that had a DSM focus. It is not surprising that the Chronic Pain topic showed lower prevalence in abstracts with DSM focus given that the most recent edition of DSM does not include a pain-specific disorder (Katz et al., 2015).

COMPARISONS OF PREVALENCE OF DSM FOCUSING IN ACT RCTS IN LMICS AND HICS

We next examined if the focus on DSM in the articles was related to whether the article was published in an indexed journal or not and if that differed across LMIC and HIC sources. Tests of (non)-independence of DSM focus and indexing showed that using all publications across all years from all countries, there was no association between DSM focus and indexing in the entire sample (top panel of Figure S9, Section 11 of Supplementary Materials) or in the LMIC publications alone (bottom panel of Figure S9), but there was a statistically significant association in the HIC publications (middle panel of Figure S9). There was a greater proportion of articles that did not focus on DSM than articles that did focus on the DSM categories in the indexed subset, whereas the difference between the proportions of articles focusing on DSM vs. not was not reliable in the nonindexed subset of the HIC papers. The higher proportion of non-DSM focus articles in indexed journals may reflect that ACT research has had a transdiagnostic focus.

Another interesting pattern emerged when we tested the dependence of DSM focus on the year of publication. We first focused on the full sample

including all publications across all years from all countries, then on HIC publications from all available years, then HIC publications for years 2011 and 2023 (similar to the range of years in the LMIC subset), and then all available years in the LMIC ones. The full sample results (top panel of Figure S10, Section 12 of Supplementary Materials) show that the number of articles that focus on the DSM has decreased over time. This effect appears to be largely due to a similar trend in LMICs (bottom panel). DSM focus and year of publication were unrelated for HIC papers (the two panels in the middle), regardless of whether we looked at all years or focused on years 2011 to 2023, the time span which was comparable to the years of publications of LMIC papers.

Finally, we examined (non)-independence of indexing and year of publication (Figure S11, Section 13). Looking at the entire sample combined, there was a growing focus on nonindexed articles, but that was largely due to the growth of nonindexed articles in LMICs. In the HIC subset, there was an opposite trend of decline in nonindexed articles over time, which was true regardless of whether focused on all available years or restricted the range to 2011 to 2023.

QUALITATIVE EXAMPLES OF THE PROBLEM OF NOT INDEXING LMIC RESEARCH

In order to characterize in a more qualitative way how a lack of indexing can marginalize the LMIC voice, we first selected the largest nonindexed study in LMICs. The largest nonindexed Chinese study was focused on orthodontic compliance in adolescents (Gang et al., 2016). A total of 400 adolescent orthodontic patients were randomly treated with conventional orthodontic treatment, or that plus ACT. After treatment, there was a statistically significant difference between the two groups in maintaining good oral hygiene, intactness of attachment to the dental appliance, and compliance with the proper wearing of an adjunct appliance. Differences in secondary mental health outcomes were also found. The authors concluded that ACT can improve and shorten the orthodontic treatment process. This study is of particular interest because the number of ACT studies on dental care is limited and because of the use of objective measures.

We then examined LMIC abstracts for a topic in which nonindexed LMIC studies constituted significantly higher expected topic proportion estimates than indexed sources: Resilience and Adjustment. These studies had low sample sizes ($N \sim 30$; $n \sim 15$ per arm) but found that an ACT interven-

tion successfully promoted resilience and reduced stress in female hospital employees (Zarinfar et al., 2019) and fostered resilience and cognitive flexibility in prisoners convicted of nonfinancial crimes (Valizadeh et al., 2020). These small studies add to the literature by focusing on underrepresented populations. From a meta-analytic framework (IntHout et al., 2016), the cumulative effect of small studies can be substantial, a point we return to in a later section focusing on sample size as a proxy for quality.

IS NONINDEXED LMIC RESEARCH “LOWER QUALITY”? THE EXAMPLE OF SIZE OF THE SAMPLE

A common concern about LMIC research is that it is “lower quality”—a criticism that is especially likely when dealing with journals that are not indexed since “quality” is claimed to be a criterion by indexing companies. There is no doubt that traditional indications of research quality are fostered by external funding, which is far more likely in HICs than in LMICs, and for that reason alone some quality indicators likely vary across the world and between journals that are indexed and those that are not. That being said, when studies are done in volume, particular limitations may factor out. An instance of this, and one that is easy to consider in the present context, is sample size. Lower powered studies will generally produce more variable results considered study by study but when viewed overall (e.g., all using meta-analytic techniques) a series of modestly sized studies is known to *reduce* error rates in the conclusions drawn relative to a single well-powered trial (IntHout et al., 2016). This simple fact is a major reason to worry about the scientific cost of ignoring LMIC research and to consider whether a lack of indexing is sweeping away attention to modest but cumulatively helpful research.

We examined this issue by dividing our sample of RCTs in a 2 by 2 array of HIC vs. LMIC and indexed vs. nonindexed publications. With LMIC studies (including the ones for which English abstracts were not available for our STM analysis), 399 were nonindexed, 63 were indexed. For HICs, 89 were nonindexed, 463 were indexed. For each study the number of participants per arm of the study were calculated. For example, a study with 99 participants comparing ACT to traditional CBT, with a waitlist control, would be considered a three-arm study, with an N of 33 per arm. These outcome data were subjected to an ordinary least squares regression analysis (equivalent to an analysis of variance) that considered country type (HIC

vs. LMIC), indexing of the journal (indexed vs. nonindexed), the interaction of the two, and year of publication.

Study size was not predicted by indexing but it was by country type and their interaction, and by the years since publication as studies have grown in size over time. (See Section 3 of Supplementary Materials for additional narrative details of the results, and Figure S12 for a visualization.) On average, indexed HIC studies had two to three times as many participants per arm as the other studies, but a lack of indexing was not associated with smaller studies in LMICs. Furthermore, meta-analyses that rely solely on indexed studies (as would be typical) would miss 86% of the LMIC research but only 16% of the HIC research. The advice to consider small studies in meta-analyses (IntHout et al., 2016) would thus be difficult to implement in ways that did not stifle the voice of LMIC researchers unless the challenge of indexing is solved.

CITATION IMPACT OF HIC VS LMIC RESEARCH, INDEXED AND NONINDEXED

To examine the citation impact of the different categories of research articles, three studies were randomly selected from each of the four categories of country and indexing (HIC nonindexed, HIC indexed, LMIC nonindexed, LMIC indexed) from the Hayes and King (in press) database for each year from 2015 to 2022. This kind of block randomization is necessary because more recent research is generally likely to be less well cited, thus the largest equally sized blocks across the largest range of years were selected. Randomization was done by selecting 3 studies from each block with blocks defined by the combination of indexing status, country income group, and publication year without replacement (using Python's NumPy library). Using earlier years led to missing values in some groups which is why sampling began in 2015; requiring more than three studies per category also created imbalances. Citations for these 96 randomly selected studies were gathered from Google Scholar on March 5, 2024.

See Section 3 of Supplementary Materials for the details of an ordinary least squares regression analysis with year since publication as a linear regressor (equivalent to an analysis of covariance) that considered country type (HIC vs LMIC), indexing (indexed vs nonindexed sources), and their interaction. After accounting for years since publication, citations were predicted by indexing, but not by country type, nor the interaction of country type and indexing. (See Figure S12 for a

visualization of predicted marginal means.) Indexed articles from LMICs received 410% more citations per article on average than nonindexed articles; for HICs, indexed articles received 482% more citations per article on average than nonindexed articles.

IMPACT OF STUDY QUALITY ON CITATIONS, DIFFERENCES BETWEEN LMIC AND HIC PUBLICATIONS

Theoretically, one would expect that studies of higher scientific quality would garner more citations. However, due to the lower overall study visibility within LMICs, it is possible that this relationship may not hold for papers published within LMIC journals. Using our only available measure of study quality as a proxy—sample size per study arm—we tested this possibility by performing two separate ordinary least squares regressions testing the effect of sample size per study arm on study citations: one within the HIC papers and one within the LMIC papers from the block randomized sample described above. (See details in Section 3 of Supplementary Materials.) After controlling for years since publication and indexing status, higher sample size per study arm was positively associated with higher citations. Within LMIC papers, after controlling for years since publication and indexing status, sample size per study arm did not predict citations. These findings indicate that although appearing in an indexed journal is important for boosting the visibility of studies from LMICs, sample size (per study arm) as an indicator of higher scientific quality is not predictive of greater visibility. This is consistent with our previous results where sample size was not predictive of indexing in LMICs, as it was in HICs.

Conclusion

The LMIC RCT base in ACT is substantial and varied, covering nearly 500 studies across a wide range of topics. Despite its size, a major finding of the present study is that a lack of indexing is marginalizing the voice of LMICs and non-English HICs, at least in the ACT RCT literature. Such marginalization could be due to an active stifling of voices (e.g., rejecting high-quality LMIC studies), to passive neglect (ignoring LMIC studies in a literature review), or to country-specific practices (e.g., LMIC countries encouraging a student to publish in a native-language journal to get a degree). Hayes and King (in press) found that LMICs contribute over 45% of the world RCTs on ACT, but because the great majority of nonin-

dexed studies come from LMICs (over 83%), much of this work is invisible to most researchers and practitioners across the world.

The present study suggests that LMIC research reflects in many ways the topic and trends of HIC research, but without consideration of LMIC studies, these topics would be harder to quantify objectively. Our results also show that LMIC ACT RCTs are less cited worldwide, especially if nonindexed. Said in another way, by marginalizing the voice of LMIC researchers, it is harder to understand ACT research in its entirety.

If this pattern is replicated in CBT and evidence-based therapy more generally, that would further show that a profound inequity that has long been known to exist has worldwide knowledge implications. There are many evidence-based reasons to underline the importance of race, ethnicity, economic status, and culture to the understanding and deployment of psychological inventions (Huey Jr et al., 2014). Some of these sources of influence can be examined in research from HICs, but they are addressed in a deeper way across different cultures around the world. It is hypocritical to call for more attention to diversity, equity, and inclusion issues across important demographic and cultural divides on the one hand and then to marginalize the voices of different cultures and communities based on language and economics on the other.

The present study examined only ACT RCTs, but as other methods and other types of research are added, the relative invisibility of LMIC research carries an increasing risk of distorting empirical comparisons across assessment and intervention methods. For example, based on research output alone ACT is apparently popular in Iran and China. If ACT is being compared to another form of CBT and research from those countries is ignored, a distorted picture is sure to result. Said more simply, the knowledge base for all forms of evidence-based intervention needs to be thought of from a worldwide mindset, and that cannot happen readily given the current state of informatics. Marginalizing voices is especially pernicious as a source of bias because researchers cannot know what they do not know.

Another example of the practical clinical cost of narrowness is in the area of religious adjustments of evidence-based procedures. For instance, there are dozens of examples of studies (mostly not RCTs; mostly from Iran) that have modified ACT using stories and metaphors from the Holy Quran (ACBS, 2022). If most Iranian research is nonindexed, what has been learned there could

be virtually invisible to the world's scientific literature, especially to non-Iranian researchers who may be interested in cultural adaptations of evidence-based procedures. Science and religion have often been needlessly looked at as disconnected traditions or even adversaries in human sciences. A more process-based approach to evidence-based intervention fosters a parallel approach: intervention science can be especially useful for delineating and fostering processes of change relevant to client goals and values, and religion is helpful for delineating and fostering specific spiritual lifestyles that might include these goals and values. ACT researchers have fostered such a parallel approach by considering how to integrate ACT methods into pastoral counseling and clerical care (see Nieuwsma et al., 2016, for a summary of that work). This in turn has allowed ACT methods to better appeal to persons of faith across the spectrum of belief systems, as is indicated by the fact that ACT is one of three evidence methods, along with motivational interviewing and problem-solving therapy, that have been adopted by the chaplaincy of the U.S. military for training (<https://www.mirecc.va.gov/mentalhealthand-chaplaincy/MHICS.asp>). Thus, by considering the LMIC research on religiously based modifications of evidence-based practices, it may become easier to reach clients across diverse religious backgrounds in all parts of the world.

There are many other ways that rectifying the biased and deficient database caused by the relative invisibility of LMIC research can have clinical implications. These include a greater understanding of the role of culture in psychological well-being, appreciation of how privilege can cause blind spots in clinicians and researchers alike, and greater clarity on as to how personal values develop, among many other clinically relevant topics. We are not claiming that mere contact with the LMIC literature alone will have a major and positive benefit in these areas, or indeed in diversity, equity, and inclusion (DEI) efforts more generally. DEI research and training will undoubtedly still be needed, but greater awareness of LMIC research sets the occasion for that to occur. An example of how relevant DEI research might do so is presented by Asnaani et al.'s (2022) response to the ACBS Task Force 2021 report (Hayes et al., 2021). Work on mental health care disparities will require greater attention to policy matters, technology, community-based research, and similar matters that DEI researchers have championed (Asnaani, 2023). But those steps all begin with greater awareness, and fostering contact with

LMIC research can only help but bolster the kind of awareness that might make a long-term difference.

There is a temptation to rationalize the invisibility of LMIC research based on “scientific quality.” Our analysis found that on some measures of quality (e.g., study size), indexing was not particularly predictive, but country of origin was. Regardless, it is a logical error to think of the total value of a line of research in purely averaging terms since, as the very word “research summary” suggests, science is a cumulative enterprise. Suppose a given area has 10 large and well-powered studies and 100 small and underpowered studies, while another area has only 10 large ones. Averaging the size of studies as an indication of proper research impact would suggest that the scientific and applied community knows *more* in the only 10-large studies case than when 100 small studies were also done. For that to be true, smaller LMIC studies would somehow need to magically *subtract* knowledge from larger HIC studies. This logical error appears to be built into human evaluation processes applied to research (see Hayes, 1983, for another example). The argument leads to classism, yet it has been commonly argued in the CBT literature (see Hayes et al., 2023, for examples and counterarguments). As this idea applies to sample size it also violates the half a century or more of development in behavioral and cognitive therapy that has long argued that very small or even single case studies also contribute to knowledge advancements if the volume of intensive small-*N* research is sufficient (Hayes et al., 1999).

The lack of linkage between our single quality indicator and indexing in LMICs might be explained by requirements of students to publish articles as a condition of receiving an advanced degree. Students may submit to journals with less impact but with more chances of getting the papers published soon. Furthermore, because language issues apply not just to authors but also to readers, these issues might lead researchers to publish in non-English journals so as to reach a wider audience within their own language community—producing a lack of correlation between sample size and citations in LMICs.

It is clear that the differences between citation rates of indexed and nonindexed studies cannot be wholly based on research quality regardless of how that concept is defined. For instance, economic sanctions against Iran undermine the ability of its citizens to be involved in worldwide scientific communication, regardless of the quality of their work. Furthermore, RCTs are arguably not the best way to understand processes of change

(Hayes et al., 2021) and thus may have been overemphasized to the detriment of progress in CBT. This possibility is especially clear as a process-based therapy (PBT) approach to evidence-based therapy strengthens (Hofmann & Hayes, 2019). Also called by several other terms such as process-based cognitive behavioral therapy (PBCBT) or process-based behavior therapy (PBBT), a process-based approach is built on the view that the core target focus of intervention science should be on the biopsychosocial processes that can be most effectively and efficiently changed to achieve a desired outcome (Hofmann & Hayes, 2019). It turns out that processes of change need to be examined idiographically first in order to be understood and applied to particular people because of the sticky problem of ergodicity (Hayes et al., 2022). That suggests that high temporal density measures are needed that can be studied first in an idiographic way, and then scaled to nomothetic generalizations provided the idiographic fit is improved (see Sahdra et al., 2024, for an example), but that may require a large number of small-*N* studies done worldwide in practice in research collaboratives, not huge RCTs in the WEIRD world.

It seems possible that processes of change can be better adjusted to fit diverse social and cultural contexts than protocols—especially if the processes involved are linked to basic principles with higher precision and scope. For example, a principle such as reinforcement may be less likely to be culturally narrow than, say, a list of agreed-upon virtues or character strengths. It is worth noting that “culture-bound syndromes” have been added to the DSM itself to recognize the fact that there are disorders that occur commonly in one culture and never in others. That same point applies to culture-bound processes of change.

OVERCOMING BARRIERS

Researchers from LMICs encounter notable obstacles when attempting to publish their work in international peer-reviewed journals. These challenges include limited funding, language barriers, often steep article processing fees (Lourenco et al., 2023), and gender disparities, among others (Shumba & Lusambili, 2021). Alongside the challenge of publishing their work, LMIC researchers also struggle with accessing published research. Despite the rise in electronic research publications offering open access in the past decade, the costs associated with processing submissions and publication have shifted onto the researchers seeking to publish, rather than the readers. For numerous researchers operating in LMICs, the Article Pro-

cessing Charges (APCs) are exorbitant, hindering the dissemination of research conducted within and pertinent to these nations (Saloojee & Pettifor, 2024).

Our data suggest that HIC studies that are non-indexed research have a hard time being noticed as well. In our dataset, much of this research is in Korean or Japanese journals that publish studies in those languages. The citation impact of these studies is often low, possibly due to language barriers. As a reflection of the problem, it is worth noting that Korean research only began being formally included in the Web of Science in 2014 (Thomson Reuters, 2014). In the context of staggering advances in artificial intelligence and increasingly sophisticated automatic translation software, it is hard to see why scientists should continue to accept language barriers as the permanent status quo to scientific information.

In the present study, we have examined how arbitrary and ethnocentric barriers are unfairly diminishing the voice of LMIC researchers and practitioners. Given the biases of indexing engines, for LMIC research to be given proper attention and due weight, affirmative steps must be taken to find, list, and analyze such research. Scientists, scientific organizations, and governments will need to work together to change how indexing is done. The evolution of open science and preprints is a positive step, and artificial intelligence tools are already rapidly diminishing the role of language barriers. These tools could be greatly expanded if professional associations sought to promote them or even to demand them. Professional societies rely on publishers of their journals, but the reverse is also true and there are few reasons to be satisfied with a world scientific culture of “English only” or “Only HICs need apply.”

Cross-cultural studies, international research, and fostering studies with a greater diversity of researchers can also be very helpful. If a team from different countries is gathered and each person does a part of the work, it is easier to avoid financial problems and language barriers while increasing article quality and extending the diversity of topics.

A number of additional actions could be taken, such as by the Association for Behavioral and Cognitive Therapies—the scientific and professional body that publishes this journal. Journal editors might be better sensitized about the importance of inclusivity as a metric when engaging with local stakeholders in LMICs communities. Scientific and professional societies might join to establish public review mechanisms to assess the extent to which

global health research stakeholders address standards that create imbalance. Taking steps to ensure author inclusivity would provide researchers from LMICs greater opportunities to share their perspectives and have their voices count (Shumba & Lusambili, 2021). International grant funding agencies could include funding for articles in their grants to subsidize the cost of publication in known and indexed outlets (Saloojee & Pettifor, 2024). Steps could be taken to increase collaboration networks between research centers in LMIC and HIC countries to help ease the impact of barriers of this kind. Professional societies need to consider “matchmaking” services for facilitating collaborative projects in which researchers from HIC and LMIC are paired based on mutual interests and availability. If researchers worked together from the beginning of research projects across the LMIC–HIC divide, it would likely help resolve many of the community isolation problems we see in the present literature.

The steps taken by ACBS in creating the database we used in this study also show that professional societies need not be inert in facing the HIC–LMIC divide-related challenges we have discussed. Thousands of hours of volunteer and staff actions over years of work have gradually created a useful, if still imperfect, worldwide resource on the ACBS website. Fostering and bringing attention to research and practical advancements is part of what professional associations do, so building global knowledge resources that apply across the HIC–LMIC divide would be a values-based extension of the work of most evidence-oriented associations.

RCT lists are only one example. As another, ACBS maintains a list of measures of mindfulness and psychological flexibility processes available in languages other than English. The website currently provides links to measures in 49 languages other than English (bit.ly/ACTmeasures). ABCT, perhaps in alliance with like-minded associations, could do something similar across the global CBT literature in all of its forms.

The data in the current study show that our knowledge regarding psychological intervention is being arbitrarily inhibited by forces that divide the world community. Every voice matters, and the time is ripe for scientists and professionals around the world to take responsibility to heal those divides.

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