Social Work Research Map – Algorithmic Visualization of Social Work Discourses

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Abstract

Purpose: This study introduces the Social Work Research Map, an interactive website designed to improve access to scholarly publications in social work. The website provides users with access to a database of nearly 25,000 journal articles from 23 social work journals.

Methods: The social work articles were analyzed and structured into 40 thematic clusters using automated text analysis. The features of the platform are illustrated by means of a use case scenario in youth services.

Results: The website offers visualization techniques and filter functions allowing users to conduct independent searches on their target topics. Users can save individual search results, and an artificial intelligence-based recommendation system suggests similar publications.

Conclusions: The Social Work Research Map is a valuable resource for navigating the rapidly expanding field of social work research. Through the website's comprehensive database and innovative features, users can easily explore and discover relevant scholarly publications in the field of social work.

Keywords: Internationalization, social work research, topic modeling, text analysis, database, machine learning

1 Introduction

In recent years, the internationalization of social work has become an integral part of higher education policy [19, 24, 26]. This change can be regarded as a consequence of the increasing interconnectedness and globalization enabled by digitalization. Although social work primarily operates within national boundaries and is often mandated through national legislation, international collaborations have become increasingly prevalent in social work research [14]. The accumulation of knowledge from different countries is believed to lead to robust evidence for social work practice or at least provide valuable insights into new developments and reflections. However, inequalities persist in the dissemination of scientific knowledge. Despite evidence that scientific knowledge production is increasingly decentralized [14], scholarly work from countries in the global south is still disadvantaged (e.g., sub-Saharan Africa) [16]. Even between western countries, social work knowledge does not easily diffuse [13]. This phenomenon can be attributed to numerous factors, ranging from cultural factors [31] to structural arguments [13].

Irrespective of these underlying factors, access to scientific knowledge fundamentally requires the awareness of its existence. In the context of advancements in digital technology, which includes search engines and databases, the fact that obtaining an overview of scientific knowledge within a specific field of interest is becoming increasingly challenging for social work students, practitioners, and researchers seems paradoxical. The vast growth in scholarly productivity is evident from the number of journals and articles published over the past 30 years [29]. Even if we consider only journal articles and exclude non-English publications, we still need to navigate through 20,000 journal articles published between 1989 and 2016 [8], in addition to the articles from at least two new journals that are launched each year. Moreover, obtaining a comprehensive overview of a particular topic within the literature is complicated by its indexing in different databases with non-intuitive web interfaces and varying search function requirements (e.g., different operating systems).

The project presented in this article aims to overcome some of these barriers to knowledge acquisition and to improve the identification and accessibility of social work research. Developed using a machine learning approach, the proposed Social Work Research Map (SWORM; www.sworm.org) provides low-threshold access to international literature by pre-structuring journal abstracts thematically for use in teaching, research, and practice.

The rest of the paper is organized as follows: First, we provide an overview of the basic functions and features of the SWORM home page. Second, we illustrate the potential of the proposed system by presenting a fictional use case involving a social worker searching for evidence-based information on drug-related intervention strategies. Third, we describe the technical details underlying the SWORM project. Finally, we discuss the limitations of SWORM and possible areas for further research and development.

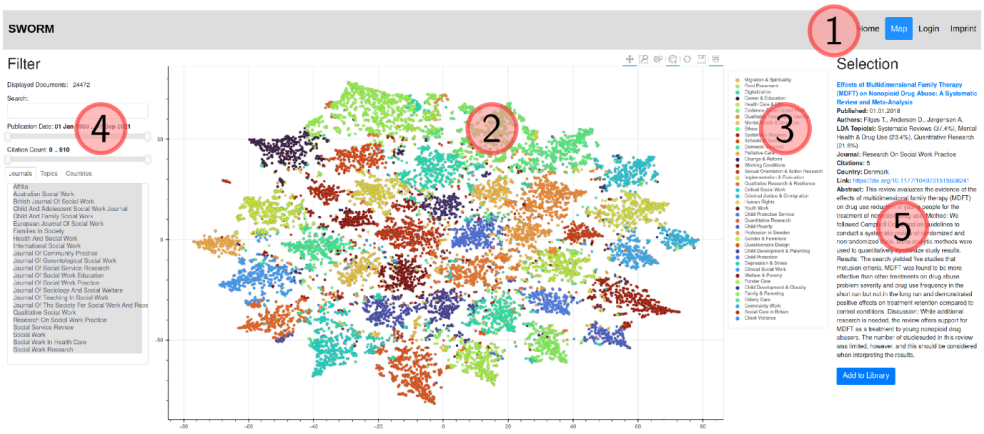

Fig. 1 Key functions of the Social Work Research Map (www.sworm.org)

2 Basic Functions of SWORM

The idea behind SWORM is to combine quantitative text analysis methods (see Section 4.3) with a web interface that allows users to analyze the dataset and identify publications on the basis of their individual interests. The SWORM database contains approximately 25,000 journal abstracts, including their respective metadata, from 23 social work journals. A detailed description of the underlying technology and methods is presented in the Section 4.

The interactive website consists of four tabs (#1 in Fig. 1). The landing page "Home" provides the background of the project. A four-minute video tutorial explains the main functions of the website and how to use it. The centerpiece is the "Map" page, which visualizes the results of topic modeling (#2 in Fig. 1). Each point on the map represents a publication, and the points are color-coded and clustered. Each color represents one of the 40 topics listed in the legend to the right of the map (#3 in Fig. 1).

Most publications cannot be assigned exclusively to one topic. For example, publications in the cluster "Qualitative Research & Identity" have thematic proximity owing to their methodological approach, although the studies usually deal with different subjects and are therefore related to other topics as well (e.g., "Child Poverty" or "Working Conditions"). Hence, the topic assignments are only a rough classification. A more specific literature search can be performed on the "Map" page by using the filter function on the left side (#4 in Fig. 1). Search terms can be entered in the search bar, and only the points/publications that are associated with the terms are displayed on the map. In addition, the search can be limited by specifying a publication date or a minimum or maximum number of citations. Users can also limit the search to specific journals, topics, or countries of origin of the first authors' affiliated institutions. The map with the selected publications can then be examined closely with the cursor.

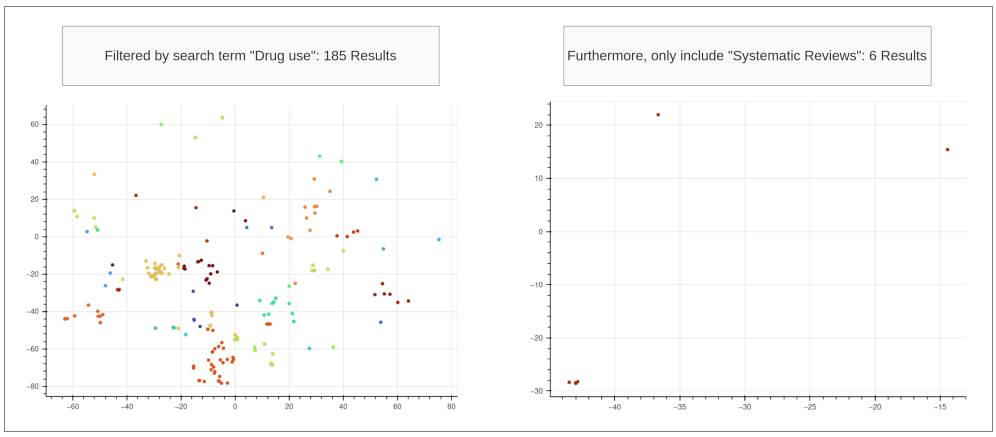

Fig. 2 Exemplary search results

For this purpose, various zoom functions can be selected from the toolbar located above the map. If the right "hover" icon is activated, touching a point with the cursor opens a window that shows the main information about the selected publication, including its abstract. Clicking on the publication permanently displays this information in the "Selection" column (#5 in Fig. 1). The page displays not only the publication data but also the results of the topic modeling ("LDA Topic(s)"). The publication selected as an example was added to the cluster "Systematic Review" because it is a systematic literature review with a probability of 37.4%. The publication is also related to the topic "Evidence-Based Social Work."

Below the "Selection" column is the "Add to Library" button that allows users to save the selected publication in an individual memory. Using this function requires a login, which mainly requires users to input a nickname and password. This function is linked to a machine learning-based recommendation system, which suggests further articles to users according to their individual libraries and thus provides additional support for literature search.

3 Applying SWORM to Practice: Drug-Related Intervention Strategies

We present a use case scenario for SWORM. Suppose Harley, a social worker in a community youth center located in a mid-sized city in the northwestern United States, needs to gather information to solve a practical problem. Drug use among young people in the city has been steadily increasing in recent years. The municipality has asked the youth center to develop an intervention strategy to respond to this situation. Using SWORM, Harley begins her research by typing "drug use" in the search box and finds 185 results.

To further refine the search, Harley limits the search to review articles by activating the "Systematic Reviews" cluster from the "Topics" tab. She obtains six results and reads the abstracts. The articles deal with treatment programs for young drug users. The first article is a systematic review on cognitive-behavioral therapies (CBT), but it concludes that there is no evidence that CBT performs better or worse than other interventions [12].

The second article is a systematic review on functional family therapy (FFT), which reports limited evidence on its effectiveness. Only one study provided numerical results on the effect of FFT on drug use reduction [10]. Another article reviews brief strategic family therapy (BSFT), finding that BSFT has mixed results on drug use but positively affects treatment retention [21]. Finally, a review on multidimensional family therapy (MDFT) shows positive short-term effects on drug use but not long-term effects [11].

Thus far, Harley has found insufficient empirical evidence to support the efficacy of CBT and FFT interventions. For BSFT and MDFT, the database is also limited, but evidence indicates longer retention in treatment programs. SWORM allows Harley to refine the search based on these findings and discover additional literature on family-based interventions.

4 Development of SWORM and Underlying Methods

SWORM was developed using a variety of methods[1]. This section introduces the database on which the service is based and the main method for structuring and mapping the data. Finally, the techniques for visualizing the results and recommender system are presented.

4.1 Journal Selection and Database

The SWORM database contains 24,472 journal abstracts, including their metadata (e.g., authors, publication year, citations), from 23 core social work journals. Abstracts were included from journals whose prestige was rated highest by social work scholars [17].[2] This list was compared with the 2019 Journal Impact Factors [6] because the study only surveyed scholars in the United States and the results are rarely associated with citation-based measures of quality [22]. However, these "citations reports" do not classify social work journals. To identify the most cited social work journals, we searched only for journals listed in the "Social Work Research Database" [29]. Doing so allowed us to add three journals[3] that were not included in the study by [17].

[1] We openly provide the source code used to retrieve, process, and provide the service: https://github.com/kkirchheim/sworm-mining; https://github.com/kkirchheim/sworm.

[2] Social Service Review, Journal of the Society for Social Work and Research, Social Work, British Journal of Social Work, Social Work Research, Journal of Social Work Education, Families in Society, Journal of Social Service Research, Qualitative Social Work, Health and Social Work, Social Work in Health Care, Journal of Sociology and Social Welfare, Affilia: Journal of Women and Social Work, Journal of Gerontological Social Work, Child and Adolescent Social Work Journal, International Social Work, Journal of Community Practice, Journal of Social Work Practice, Journal of Teaching in Social Work

[3] Australian Social Work, European Journal of Social Work, Child & Family Social Work

4.2 Database Creation

Using the Scopus Application Programming Interface (API), we programmatically collected a dataset containing all articles published in the 23 selected journals[4]. Through this API, the academic publisher Elsevier provides authorized users with a standardized way to interact with its large Scopus publication database. In our case, interaction mainly consisted of formulating queries and processing the responses. More precisely, we first retrieved a complete list of all articles published in each of the target journals between 1959 and 2021. Subsequently, we retrieved the metadata (title, author names, abstracts, publication date, etc.) for each article to populate our article database, which forms the basis for the analysis described in the following section. As interaction with Scopus requires authentication and queries are rate-limited, the entire process of identifying articles and retrieving their metadata took several days.

4.3 The Use of Topic Modeling for Topic Identification

We used topic modeling to identify the 40 social work topics available in SWORM. Topic modeling is a quantitative method used to analyze texts [25]; for our study, we employed latent Dirichlet allocation (LDA) [5]. Our forthcoming discussion provides a detailed overview of this method, including the algorithm's functionality and the methodological process involved. However, we refrain from delving into the mathematical underpinnings of LDA in this article. Interested readers can refer to the work of [5] for an in-depth understanding of the mathematical principles involved.

LDA is an exploratory technique used to identify topics from texts. In this context, exploratory implies that researchers need not provide any input to identify topics, and that words representing specific topics need not be predetermined, as is the case in basic word frequency analyses. LDA automatically produces lists of words that, in the best-case scenario, can be uniquely attributed to a topic. For example, a word list may include terms such as "evidence," "based," "practice," "empirical," and "survey" [9]; then, a label can be assigned to the resulting list. In this example, the label "evidence-based practice" may be appropriate.

LDA has two probability distributions: the probability distribution for the words in the topics and that for the topics in the documents. In SWORM, we have incorporated a field into the abstract's single view (located in the Selection column and labeled as "LDA Topic(s)") that displays the probability of a specific topic's occurrence in the selected abstract. Only those topics that exceed a certain minimum percentage probability of appearing in the summary are displayed. Throughout the project, we generated several documents for each topic and evaluated their consistency by examining the documents. However, owing to the large number of abstracts involved, we could only perform this evaluation on a visual sample basis.

One open question is why our LDA model shows 40 topics rather than 20, 33, or 149. The number of topics is determined by a parameter in the LDA algorithm, which can be influenced by the researchers. The optimal number of topics can be determined

[4]With the kind permission of Scopus, the data thus obtained may be integrated on our website.

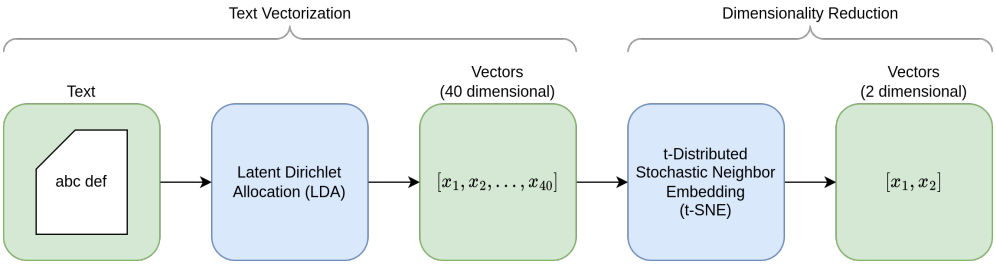

Fig. 3 Structure of the mapping pipeline: We use latent Dirichlet allocation to transform the documents to 40 dimensional vectors that approximately capture the semantics of the articles. We then further reduce the dimensionality of the data using t-distributed stochastic neighbor embedding to represent each article as a two-dimensional vector that can be plotted directly onto a flat map while preserving most of the semantic similarities.

through different proposals and evaluation methods found in the literature [4, 27, 30]. We chose the approach by [30] as it considers two important metrics: coherence and exclusivity. The coherence measure determines the closeness of a topic based on the co-occurrence of words within topics. The exclusivity metric considers whether a word is more likely to appear in one topic than in another [3].

The optimal number of topics results from the combination of both metrics. To determine this number for SWORM, we calculated 10 models and compared the values of coherence and exclusivity. Apart from using quantitative metrics to determine the optimal number of topics, performing a qualitative analysis of the results is equally important. For example, when we initially used a relatively low number of topics, we noticed that some important topics were missing or that two topics were combined into one word list. Conversely, when we used a higher number of topics, the topics became increasingly specific and difficult to interpret. Therefore, in addition to comparing different models based on quantitative metrics, we randomly reviewed the abstracts and assessed the meaningfulness of the topics.

4.4 Mapping Articles in Two Dimensions

The visualization of the articles as a flat map (i.e., on a two-dimensional plane) such that articles that are semantically similar are mapped close to one another is a challenging problem because of several factors. First, capturing the semantics of articles in a representation that allows the algorithmic computation of the similarity of two articles is nontrivial. Second, finding a two-dimensional mapping of articles that preserves their similarities is computationally challenging because the number of similarity relations between articles grows rapidly. For example, for 24,000 articles, approximately 288 million article-to-article similarities may need to be considered when searching for a suitable map.

The solution used in this work is depicted in Fig. 3. As described above, we initially used LDA to automatically extract the latent semantics from the journal articles. Doing so allowed us to represent each article as a vector with 40 dimensions, which

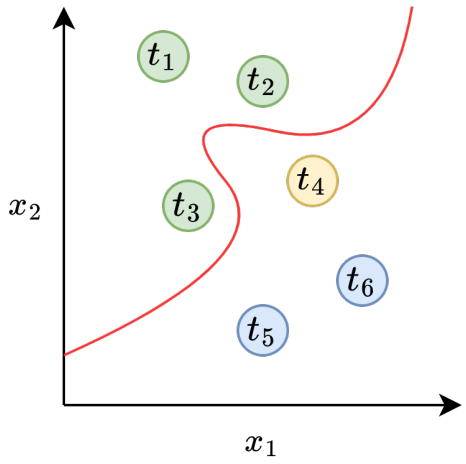

Fig. 4 Sketch of the principle underlying the recommendation engine. A machine learning algorithm called support vector machine finds a boundary that separates the articles in a user's library (green) from all other articles. Articles that are not in the library and are close to the boundary (yellow) are then recommended to the user.

can be seen as a list of 40 values. Specifically, each value represents the probability of the article belonging to a particular topic. We then applied a computationally efficient algorithm called t-distributed stochastic neighbor embedding (t-SNE) [33] to find a two-dimensional representation of the articles that approximately preserves their (local) similarities. This two-dimensional representation allowed us to plot each article to a point in a flat map such that the articles with similar semantics were mapped close to one another while articles with different semantics were mapped to different regions.

4.5 Recommendation Engine

SWORM features a recommendation engine that can provide personalized recommendations to users. The general idea is depicted in Fig. 4. The machine learning model underlying this system is a support vector machine [7], which can be used to solve a two-class classification problem wherein two groups are to be distinguished. In our case, these groups consist of the items that a user adds to their personal library (green) and the items that they have not added (yellow and blue). For this purpose, a decision boundary (red) is calculated so that green points are (as far as possible) on one side of the boundary while others are on the other side. Articles not in the library and that are closest to this decision boundary (yellow) are recommended to the users as they tend to be similar to the green articles.

5 Conclusion

Social work is a profession that is highly dependent on contextual information and is thus largely tied to national boundaries. However, research has acknowledged the importance of broadening social work knowledge to include international professional

discourses, which should be integrated into the education of social workers [19]. The SWORM project aims to provide an accessible platform for students, researchers, and practitioners to access international social work literature. Using topic modeling, SWORM can uncover semantic structures and identify relevant texts for social work.

One might question the potential value of SWORM for research and social work practice given the existence of large literature databases and search engines (e.g., Google Scholar). In particular, these existing tools have been shown to have low precision in terms of the search results and are thus difficult to use when searching for relevant publications [15]. By contrast, SWORM provides highly precise results by exclusively searching social work journal articles. The project's greatest potential lies in its unique fusion of topic modeling and visualization techniques. While the analysis of topic modeling typically necessitates knowledge of a programming language, the incorporation of an intuitive web interface together with a visualization technique enables even non-experts to analyze the underlying data and comprehend vast amounts of information. Users can conveniently visualize publications associated with their respective fields of interest with just one command and further filter these publications on the basis of selected parameters, such as citation frequency.

The development of SWORM is an example of the increasing entry of artificial intelligence into social work. Corresponding technologies are discussed and applied not only to social work research but also in practice (for a comprehensive overview, see [32]). The related possibilities to make certain human processes (e.g., risk assessment in child protection) increasingly effective and efficient [18] should be reflected critically against the background of existing problems with these technologies [20]. Although SWORM may not initially appear to be problematic, the integration of a recommender system does raise ethical concerns. This system limits the exposure of users to certain knowledge and could be viewed as an active participant in shaping individual preferences and identity formation [23]. However, users of SWORM can opt out of the personal "Library" feature and still use the platform without utilizing the recommender system.

5.1 Limitations and Perspectives

We believe that the methodological approach and the resulting product in our study have great potential for training and practice, but some questions and criticisms must be addressed. Although our goal is to promote access to international literature, SWORM does not provide direct access to full texts, and paywalls cannot be circumvented. Instead, users are provided with digital object identifier (DOI) links to the publications, which redirect users to the actual sources that may be open access publications.

We should also note that although this project aims to promote international knowledge, the data are concentrated on only a few countries. This limitation is due to our focus on high-impact journals, which typically publish articles in English, and the corresponding publication culture and opportunities in certain countries. As a result, 61% of all publications (15,038 publications) are written by first authors affiliated in the United States.

Finally, the SWORM homepage does not meet website accessibility standards and can thus lead to the exclusion of certain users. The use of pre-programmed components in the creation of the website, such as Python and JavaScript packages, made it difficult to create a barrier-free website independently. While resources were not available to create a barrier-free website in this project, future efforts may consider other options to address this limitation. Additionally, the sustainability of the project is a concern as scientific discourse is constantly evolving. The relevance of journals can change over time, and new articles are continually being published. The data could indeed be updated, but the use of methods such as t-SNE may not be sufficiently stable, and the map could change significantly. A decision on the implementation of these options has not been made as practical experience with the use of SWORM needs to be gathered first.

Declaration of Conflicting Interests

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References

[1] Abrams, L. S. (2010). Sampling 'hard to reach' populations in qualitative research: The case of incarcerated youth. *Qualitative Social Work*, 9(4), 536–550. https://doi.org/10.1177/1473325010367821

[2] Austin, A. M., Macgowan, M. J., & Wagner, E. F. (2005). Effective family-based interventions for adolescents with substance use problems: A systematic review. *Research on Social Work Practice*, 15(2), 67–83. https://doi.org/10.1177/1049731504271606

[3] Bischof, J. M., & Airoldi, E. M. (2012). Summarizing topical content with word frequency and exclusivity. In *Proceedings of the 29th International Conference on Machine Learning*, UK, 9–16.

[4] Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM*, 55(4), 77–84. https://doi.org/10.1145/2133806.2133826

[5] Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, 3(1), 993–1022.

[6] Clarivate Analytics. (2019). Journal citations reports. https://impactfactorforjournal.com/journal-impact-factor-list-2019/

[7] Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, 20, 273–297. https://doi:10.1007/BF00994018

[8] Eckl, M., Ghanem, C., & Löwenstein, H. (2019). The evolution of social work from disconnected groups to a scientific community: A social network analysis. *The British Journal of Social Work*, 49(2), 428–447. https://doi.org/10.1093/bjsw/bcy050

[9] Eckl, M., Ghanem, C., & Spensberger, F. (2021). Mapping discourses in social work research – A topic modeling approach. *International Journal of Global Social Work*, 4(1), 1–6. https://doi.org/10.15344/ijgsw/2021/118

[10] Filges, T., Andersen, D., & Jørgensen, A.-M. K. (2018a). Functional family therapy for young people in treatment for nonopioid drug use: A systematic review. *Research on Social Work Practice*, 28, 131–145. https://doi.org/10.1177/1049731516629802

[11] Filges, T., Andersen, D., & Jørgensen, A.-M. K. (2018b). Effects of multidimensional family therapy (MDFT) on nonopioid drug abuse: A systematic review and meta-analysis. *Research on Social Work Practice*, 28(1), 68–83. https://doi.org/10.1177/1049731515608241

[12] Filges, T., & Jorgensen, A.-M. K. (2018). Cognitive–behavioral therapies for young people in outpatient treatment for nonopioid drug use. *Research on Social Work Practice*, 28(3), 363–385. https://doi.org/10.1177/1049731516629803

[13] Ghanem, C., Lawson, T. R., Pankofer, S., Maragkos, M., & Kollar, I. (2017). The diffusion of evidence-based practice: Reviewing the evidence-based practice networks in the United States and German-speaking countries. *Journal of Evidence-Informed Social Work*, 14(2), 86–118. https://doi.org/10.1080/23761407.2017.1298074

[14] Gui, Q., Liu, C., & Du, D. (2019). Globalization of science and international scientific collaboration: A network perspective. *Geoforum*, 105, 1–12. https://doi.org/10.1016/j.geoforum.2019.06.017

[15] Gusenbauer, M., & Haddaway, N. R. (2020). Which academic search systems are suitable for systematic reviews or meta-analyses? Evaluating retrieval qualities of Google Scholar, PubMed, and 26 other resources. *Research Synthesis Methods*, 11(2), 181–217. https://doi.org/10.1002/jrsm.1378

[16] Hodge, D. R., & Kibirige, K. (2022). Addressing the global inequality in social work research: Challenges, opportunities, and key insights and strategies in sub-Saharan Africa. *Social Work Research*, 46(1), 84–92. https://doi.org/10.1093/swr/svab020

[17] Hodge, D. R., Yu, M., & Kim, A. (2020). Assessing the quality and prestige of disciplinary social work journals: A national study of faculty perceptions. *Research on Social Work Practice*, 30, 451–459. https://doi.org/10.1177/1049731519890402

[18] Kissos, L., Goldner, L., Butman, M., Eliyahu, N., & Lev-Wiesel, R. (2020). Can artificial intelligence achieve human-level performance? A pilot study of childhood sexual abuse detection in self-figure drawings. *Child Abuse & Neglect*, 109, 104755. https://doi.org/10.1016/j.chiabu.2020.104755

[19] Laging, M., Spilgies, J., & Waldenhof, B. (2017). Promoting international issues in social work education: A German case analyzed. *European Journal of Social Work*, 20, 337–348. https://doi.org/10.1080/13691457.2017.1283585

[20] Landau, A. Y., Ferrarello, S., Blanchard, A., Cato, K., Atkins, N., Salazar, S., Patton, D. U., & Topaz, M. (2022). Developing machine learning-based models to help identify child abuse and neglect: Key ethical challenges and recommended solutions. *Journal of the American Medical Informatics Association*, 29, 576–80. https://doi.org/10.1093/jamia/ocab286

[21] Lindstrøm, M., Filges, T., & Jørgensen, A.-M. K. (2015). Brief strategic family therapy for young people in treatment for drug use. *Research on Social Work Practice*, 25(1), 61–80. https://doi.org/10.1177/1049731514530003

[22] Hodge, D. R., Yu, M., & Kim, A. (2021). Ranking Disciplinary Social Work Journals: Comparing Faculty Perceptions With Two Citation-Based Approaches. *Journal of the Society for Social Work and Research*, 12(1), 109-129. https://doi.org/10.1086/713306

[23] Milano, S., Taddeo, M., & Floridi, L. (2020). Recommender systems and their ethical challenges. *AI & Society*, 35(4), 957-967. https://doi.org/10.1007/s00146-020-00950-y

[24] Mapp, S., & Gatenio Gabel, S. (2019). Educating students on international social work issues in U.S. social work programs: How is it done? *Journal of Social Work Education*, 55, 238–250. https://doi.org/10.1080/10437797.2018.1513881

[25] McFarland, D. A., Ramage, D., Chuang, J., Heer, J., Manning, C. D., & Jurafsky, D. (2013). Differentiating language usage through topic models. *Poetics*, 41, 607–625. https://doi.org/10.1016/j.poetic.2013.06.004

[26] McRell, A. S., & Grace, B. L. (2023). Social work, social justice, and Americentrism by design: Transnationalism in United States social work education. *Higher Education Research & Development*, 42, 397–412. https://doi.org/10.1080/

07294360.2022.2052816

[27] Mimno, D., Wallach, H., Talley, E., Leenders, M., & McCallum, A. (2011). Optimizing semantic coherence in topic models. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*, UK, 262–272.

[28] Moore, S. E. (1992). Cultural sensitivity treatment and research issues with black adolescent drug users. *Child and Adolescent Social Work Journal*, 9, 249–260. https://doi.org/10.1007/BF00755864

[29] Perron, B. E., Victor, B. G., Hodge, D. R., Salas-Wright, C. P., Vaughn, M. G., & Taylor, R. J. (2017). Laying the foundations for scientometric research: A data science approach. *Research on Social Work Practice*, 27, 802–812. https://doi.org/10.1177/1049731515624966

[30] Roberts, M. E., Stewart, B. M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S. K., Albertson, B., & Rand, D. G. (2014). Structural topic models for open-ended survey responses. *American Journal of Political Science*, 58, 1064–1082. https://doi.org/10.1111/ajps.12103

[31] Shaw, I. (2014). A science of social work? Response to John Brekke. *Research on Social Work Practice*, 24, 524–526. https://doi.org/10.1177/1049731514543408

[32] Tambe, M., & Rice, E. (Eds.). (2018). *Artificial Intelligence and Social Work*. Cambridge University Press.

[33] Hinton, G., & Roweis, S. (2002). Stochastic neighbor embedding. In S. Becker, S. Thrun, & K. Obermayer (Eds.), *Advances in neural information processing systems 15* (pp. 833–840). MIT Press.