Leveraging AI to Streamline Systematic Reviews: A Case Study with ASReview

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Introduction/Need for the Innovation

Literature reviews are essential foundations to help researchers advance the science knowledge pool by building on previous findings (Guillaume, 2019). One of the common literature review techniques is a systematic review approach. The systematic review technique is often used in social science research. It involves a structured approach to retrieving and screening literature to synthesize evidence effectively. In the context of agriculture, this process is crucial for informing policy, practice, and future research by providing a comprehensive overview of existing scholarships. Researchers often follow the PRISMA guidelines for academic reporting of their systematic reviews (Moher et al., 2009). However, challenges such as methodological complexity, bias in the selection of search strategies, diversity of databases, and relying solely on human labor to review the literature may affect the quality and reliability of the results of systematic reviews. In addition, conducting a systematic review can be time-consuming and labor-intensive (Neeleman et al., 2024), particularly in the screening stage of this process when relevant studies are identified for inclusion. The manual selection of articles is time-consuming and prone to human error, complicating the screening process. Fortunately, rapid advances in artificial intelligence (AI) are opening new avenues to streamline and automate certain aspects of the systematic review process, potentially reducing the time and effort required and improving reliability by reducing human error. We present an application of an open AI tool named ASReview (van de Schoot et al., 2021) used in the title and abstract screening of a systematic review to accelerate the process, transparency, and accuracy of the existing screening stage and overall review.

How it Works/Methodology

The ASReview tool leverages machine learning to assist researchers in the title and abstract screening stage of systematic reviews. ASReview, developed by the ASReview Innovation Lab at Utrecht University (van de Schoot et al., 2021), is an open-source tool designed to label large collections of text documents systematically. It incorporates a “Human-in-the-Loop approach”, where human judgments are combined with machine learning to guide the decision-making process. Studies have demonstrated the tool's potential to reduce the time and effort required for systematic reviews (Admase et al., 2024; Quan et al., 2024; Romanov et al., 2024).

The screening process using ASReview can be broken down into four main steps. First, the reviewers input the bibliographic data, including the publications titles, author(s), abstracts, and the digital identifier (DOI). In the next step, a small set of labeled studies, marked as relevant or irrelevant by the researchers, is used to train the ASReview algorithm model. The third step involves reviewers manually reviewing and labeling the first 10 to 15 % of the articles as most relevant provided by the model, helping to refine the model's predictive accuracy. After confirming that no additional relevant articles are likely, the remaining literature is excluded

from further screening. This process streamlines the review, allowing for a more efficient and transparent selection of studies.

Results to Date

A systematic review was conducted to test the ASReview tool's effectiveness on the complexity of technology adoption in precision agriculture. The review aimed to reveal trends in the diffusion of precision agriculture technologies across different contexts. Literature was sourced from four databases: CAB Abstracts, Agricola, Environment Complete, and Web of Science, using search strings relevant to the research question. This yielded 5,601 publications. After applying the inclusion and exclusion criteria, 3,624 publications remained for screening with ASReview. The authors prepared a labeled set of 33 publications, which included relevant and irrelevant studies, to train the ASReview model. The authors then reviewed the first 15.6% (n = 567, N =3,624) of publications provided by the model, identifying 26 relevant articles and 538 irrelevant ones. This process provided a refined dataset for the second round of model training. In the final stage, the authors manually screened an additional 364 publications (10% of the total), confirming their irrelevance. At the conclusion of the process, 28 articles were identified as relevant, while 931 were self-excluded and 2,664 were automatically excluded. These results demonstrate the potential of ASReview to enhance the efficiency of systematic reviews.

Future Plans/Advice to Others

The successful application of ASReview in this systematic review highlights the potential for further exploration of AI-based tools in academic research. Moving forward, the authors plan to evaluate how the ASReview tool performs compared to other AI-based systematic review tools. For researchers considering the adoption of AI-driven tools for systematic reviews, the primary recommendation is to start with a clearly defined set of inclusion and exclusion criteria to train ML effectively. Additionally, it is critical to iteratively refine the model through manual input to maximize the efficiency and accuracy of the screening process.

Costs/Resources Needed

The ASReview tool can be incorporated into a systematic review process at no financial cost, as it is a free, open-source AI tool available to the academic community. However, successful implementation requires access to sufficient computational resources, such as a reliable computer and a basic knowledge of Python, as it is built into this programming language. Additionally, researchers will need access to academic databases and bibliographic software to compile the dataset for input into ASReview. Finally, human resources are another essential component. Researchers must be actively involved in labeling studies, refining the model, and overseeing the screening process, even though ASReview can significantly reduce the time and labor required for manual article screening.

References

Adamse, I., Eichelsheim, V., Blokland, A., & Schoonmade, L. (2024). The risk and protective factors for entering organized crime groups and their association with different entering mechanisms: A systematic review using ASReview. *European Journal of Criminology*, *0*(0). https://doi.org/10.1177/14773708241250278

Guillaume, L. (2019). Systematic literature reviews: An introduction. *Proceedings of the Design Society: International Conference on Engineering Design* 1(1),1633–1642. https://doi.org/10.1017/DSI.2019.169

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analysis: The PRISMA statement. *BMJ*, 339. https://doi.org/10.1136/bmj.b2535

Neeleman, R., Leenaars, C. H. C., Oud, M., Weijdema, F., & van de Schoot, R. (2024). Addressing the challenges of reconstructing systematic reviews datasets: A case study and a noisy label filter procedure. *Systematic Reviews*, *13*, 69. https://doi.org/10.1186/s13643-024-02472-w

Quan, Y., Tytko, T., & Hui, B. (2024). Utilizing ASReview in screening primary studies for meta-research in SLA: A step-by-step tutorial. *Research Methods in Applied Linguistics*, *3*(1), 100101. https://doi.org/10.1016/j.rmal.2024.100101

Romanov, S., Siqueira, A. S., de Bruin, J., Teijema, J., Hofstee, L., & van de Schoot, R. (2024). Optimizing ASReview simulations: A generic multiprocessing solution for 'light-data' and 'heavy-data' users. *Data Intelligence*, 1-19. https://doi.org/10.1162/dint_a_00244

van de Schoot, R., de Bruin, J., Schram, R., de Boer, J., Weijdema, F., Kramer, B., Huijts, M., Hoogerwerf, M., Ferdinands, G., Harkema, A., Willemsen, J., Ma, Y., Fang, O., Hindriks, S., Tummers, L., & Oberski, D. L. (2021). An open source machine learning framework for efficient and transparent systematic reviews. *Nature Machine Intelligence, 3*, 125–133. https://doi.org/10.1038/s42256-020-00287-7