

# ProfOlaf: Semi-Automated Tool for Systematic Literature Reviews

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## Abstract

Systematic reviews and mapping studies are critical for synthesizing research, identifying gaps, and guiding future work, but they are often labor-intensive and time-consuming. Existing tools provide partial support for specific steps, leaving much of the process manual and error-prone. We present ProfOlaf, a semi-automated tool designed to streamline systematic reviews while maintaining methodological rigor. ProfOlaf supports iterative snowballing for article collection with human-in-the-loop filtering and uses large language models to assist in analyzing articles, extracting key topics, and answering queries about the content of papers. By combining automation with guided manual effort, ProfOlaf enhances the efficiency, quality, and reproducibility of systematic reviews across research fields. A video describing and demonstrating ProfOlaf is available at: <https://youtu.be/4noUXfcmxsE>

## CCS Concepts

• **Information systems** → **Information retrieval**; **Data management systems**; • **Computing methodologies** → *Information extraction*.

## Keywords

Systematic Literature Reviews, Automation, LLM

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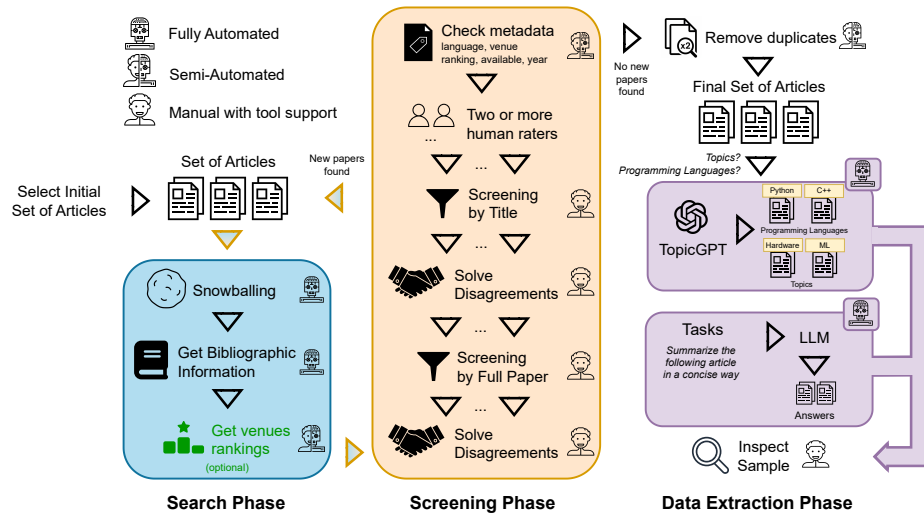
## 1 Introduction

Systematic literature reviews and mapping studies play an essential role across research fields, as they organize and synthesize existing knowledge, providing a structured overview that highlights established findings, identifies gaps, and indicates promising directions for future research. Unlike other forms of literature reviews, systematic reviews hold particular scientific value because they follow a transparent, well-defined, and unbiased methodology [4].

Despite their value, conducting systematic reviews is labor-intensive and time-consuming [16, 18]. The process typically requires conducting broad and comprehensive searches in multiple academic databases, followed by careful filtering of large volumes of articles against strict inclusion and exclusion criteria. After the collection is complete, the reviewers must also inspect and analyze the selected studies in depth, identify recurring research topics, and formulate answers to predefined research questions. Each of these steps demands sustained effort and precision.

Several methods and tools have been proposed to automate or support various steps of the systematic review process [5, 16]. Existing solutions, such as reference managers or search engines, offer only partial assistance, leaving key tasks manual, time-consuming, and error-prone, reducing efficiency and reproducibility [9]. More advanced approaches, such as AI-based tools, have shown promising results [5], but remain fragmented. Although these tools exist for individual steps of the process, no solution provides comprehensive support at all stages. Furthermore, achieving a sensible balance between manual effort and tool assistance is essential to ensure that precision is not compromised in the pursuit of reducing effort.

In response to these requirements, we propose ProfOlaf, a semi-automated tool designed to support and streamline the review process. ProfOlaf implements a structured methodology that adheres to established guidelines for systematic reviews. The methodology was designed with the goal of reducing human effort to the greatest extent possible. For the collection phase, ProfOlaf uses an iterative snowballing process to collect relevant articles, with each iteration involving human filtering supported by our tool. In the analysis phase, ProfOlaf integrates large language models (LLMs) to ease the analysis of the collected articles, enabling users to extract key topics from each article and query the model regarding its contents.



**Figure 1: Overview of the ProfOlaf methodology.** The *search phase* begins with an initial set of articles. Snowballing is applied, bibliographic information is retrieved, and venues may be optionally ranked. In the *screening phase*, article metadata is checked. Two or more human raters screen the articles by title and by full paper, with disagreements resolved collaboratively. This cycle continues until no new articles are identified. Duplicates are removed to form the final set of articles. In the *data extraction*, TopicGPT categorizes content into research topics, and LLM-based question answering is employed to extract structured insights. Manual inspection complements this step, ensuring a consolidated and reliable final set of extracted data.

ProfOlaf can assist researchers in conducting systematic reviews, thereby enhancing both the quality and the volume of such studies. ProfOlaf is open source and available at <https://github.com/sr-lab/ProfOlaf>, along with the experiments described in our evaluation.

## 2 ProfOlaf Overview

ProfOlaf is a Python tool with a structured and repeatable methodology for conducting systematic reviews, illustrated in Figure 1. The tool follows a methodology inspired by the guidelines proposed by Wohlin [17]. The subsequent sections provide a detailed explanation of each step of the pipeline.

### 2.1 Initial Setup

To setup ProfOlaf the user starts by defining a file containing an initial set of article titles. These articles are previously selected by the user and can be obtained through, for instance, a previous literature review on the topic being handled. The tool generates a database that stores all the metadata of the articles as well as the intermediate states of each article during the search.

### 2.2 Snowballing

We chose snowballing as our search method, as prior studies show it performs as well as or better than database searches [3, 8].

After populating the database with the initial set of articles, ProfOlaf retrieves either the citations (*forward snowballing*), the references (*backward snowballing*), or both, for each article. The tool then compiles the bibliographic information for all the articles. Currently, ProfOlaf obtains article data from Google Scholar [6], Semantic Scholar [15], and DBLP [14]. However, the tool has been designed to ease the integration of additional search sources.

### 2.3 Metadata Screening

Subsequently, ProfOlaf filters the retrieved articles using the metadata collected in the preceding step. Filtering criteria include venue ranking, publication year, and language, all of which are optional. Kitchenham et al. have recommended such practical criteria to refine the selection of articles [10].

When the venue-ranking filter is applied, the user must first execute the step that assigns a ranking to all the venues present in the collected articles. To help the user with this manual task, ProfOlaf first uses cosine similarity to find venues previously ranked that are similar to the one being classified. Then, the tool searches for the venue in venue ranking databases and presents the top results for each database. For each result, ProfOlaf outputs the title of the venue, its registered ranking, and the cosine similarity score of the search. Currently, ProfOlaf searches both in the Scimago webpage and in a local CORE ranking table, but this functionality is easily extendable to other venue ranking databases.

### 2.4 Manual Screening

ProfOlaf adopts the approach outlined by Wohlin [17], which recommends screening articles progressively: first the title, then the abstract, and finally the full text.

As such, in this phase, the user is prompted to further refine the results, starting with removing irrelevant articles by title and then by the full content of the article. For this, ProfOlaf presents, for each article, its title as well as a *url* where the user can access it. After each step, the tool can be used to identify and display discrepancies between the user and other reviewers' assessments. The reviewers must then discuss these disagreements and reach a consensus. The result of this discussion can then be inserted into

the tool. With manual screening completed, the resulting set of articles is used as input to the snowballing phase (Section 2.2) to start a new iteration. If a given iteration does not produce new results, ProfOlaf consolidates the findings from all iterations into a single file. As a final precaution, the tool looks for articles with similar titles and checks with the user if they are in fact the same article under a different name. With this final check completed, the user obtains the final set of articles.

## 2.5 Topic Modeling and Task Assistant

After the collection process is completed, the user can use ProfOlaf to ease the manual process of article analysis through the use of LLMs. For this, our tool provides functionality for downloading all selected articles. Then the content of the PDFs is parsed and can be provided to two analysis modules: topic modeling and our task assistant. The extracted information from both modules should be manually verified by users, either in its entirety or by sampling.

The topic modeling module uses TopicGPT [12] to gather different topics from the collection and cluster them according to those topics. TopicGPT is a prompt-based framework that uses LLMs to generate interpretable topics with natural language labels and descriptions. It enables users to group papers for deeper analysis, offering greater transparency and verifiability than traditional bag-of-words approaches. This functionality can also be useful for addressing specific research questions with closed-form answers, such as “Which programming language is being considered?”.

The task assistant module enables users to submit an article to a public-access LLM and request tasks such as key information extraction or concise, query-tailored summaries.

## 3 Evaluation

To evaluate ProfOlaf, we performed a small illustrative systematic literature review. We used the work of Ramos et al. [13] as our single seed article. We selected this paper because it won the Best Paper Award at the LLM4Code 2025 and because we are familiar with the topic of the paper.

### 3.1 Search and Screening Phase

The screening phase was carried out over seven iterations by two human raters, corresponding to the second and third authors. The following inclusion criteria were applied: (1) related to Machine Learning for Code; (2) written in English; (3) publicly available; and (4) published in a venue ranked by CORE or Scimago.

The results of all iterations are summarized in Table 1. We calculate the efficiency measure for systematic literature reviews, a metric used by Wohlin [17] in their work to evaluate the amount of noise in the search. This metric is the number of included articles relative to the total number of candidate articles examined. The efficiency by iteration and the final efficiency are both represented in Table 1. As shown in Table 1, early iterations yielded a relatively higher proportion of relevant studies, while later iterations were characterized by a substantial increase in rejections. This pattern illustrates the phenomenon of diminishing returns in the search expansion process.

**Table 1: Paper retrieval and screening results across iterations**

Iteration	Retrieved	Rejected (Metadata + Screening)	Approved	Efficiency
1	19	13 + 1	5	0.26
2	100	63 + 7	30	0.43
3	227	158 + 47	22	0.09
4	111	84 + 9	18	0.16
5	100	72 + 3	25	0.25
6	433	414 + 9	10	0.02
7	19	19 + 0	0	0
Total	1009	823 + 76	110	0.11

After screening, we obtained 111 articles, including the seed article by Ramos et al. [13]. The final set of articles consisted of 108 articles, after the removal of three duplicates.

### 3.2 Data Extraction Phase

We selected two tasks for the Topic Modeling module: identifying the programming languages explored and the topics studied; and one task for the Task Assistant module, article summarization. We perform this evaluation with gpt-5-nano.

**3.2.1 Topics Studied.** Our topic modeling module identified 17 topics. To evaluate the capability of TopicGPT in assigning correct topics to articles, we constructed a ground truth by manually labeling each article. The first and second authors received the list of topics generated and were asked to assign topics to each article. Subsequently, the raters met to resolve disagreements and establish the final list of topic assignments. The process took in total 6.45 hours. The ground truth was compared with the TopicGPT results, which achieved a precision of 0.547 and a recall of 0.650.

The raters noted several observations. The topics were generally accurate, as it was possible to assign at least one topic to the majority of articles. However, some important topics were absent from the generated set, including *Benchmark for Code Generation/Repair*, *Education*, and *Code Translation*. When comparing the module’s assignments with the manual labels, we observed that the model frequently assigned both *Code Generation* and *Automated Program Repair*, whereas the raters selected only *Automated Program Repair*, treating it as a more specific instance of the broader category. Such cases likely contributed to the observed low precision score.

**3.2.2 Programming Languages Used.** For this task, the topic modeling module identified 40 programming languages. As in the previous task, assignments were performed both automatically by the tool and manually by the same raters. However, in this case, the raters were not restricted to the module’s generated set of answers. The entire process required 3.88 hours. The module achieved an average precision of 0.590 and an average recall of 0.710.

Manual inspection of the assignments revealed that the model frequently tagged Python as one of the languages. This likely stems from the fact that many papers employ Python for data processing or model training, leading to its assignment even when it was not the language under exploration. Additionally, the model often assigned more languages than were actually relevant, suggesting a tendency toward over-assignment and a degree of hallucination.

**3.2.3 Task Assistant.** For the Task Assistant task, we asked the model for a summary of each paper. The summaries were evaluated

**Table 2: Evaluation of summary quality across 4 different criteria.**

Criterion	Mean	Std	Criterion	Mean	Std
Faithfulness	4.907	0.242	Structure	4.558	0.454
Salience	4.333	0.367	Conciseness	4.648	0.334

by two raters according to four parameters on a Likert scale from 1 to 5. The results of the evaluation are presented in Table 2.

Both raters generally agreed the summaries were accurate and free from hallucinations. *Coverage* was the lowest-scoring criterion, as some summaries did not fully capture the most important details; however, this limitation was minor (average score of 4.333). The other criteria received high scores, suggesting that the summaries were typically well-structured, easy to follow, and conveyed key points with minimal redundancy. Coherence/Structure had the highest standard deviation, indicating that the model's ability to organize ideas varied the most across summaries.

**3.2.4 Discussion.** The results indicate that while LLMs can deliver satisfactory outcomes for tasks such as summarization, more advanced models and methodologies are needed before they can be fully trusted for tasks such as topic modeling. For such cases, we argue that LLMs are best employed in a human-in-the-loop setting, either as assistants that facilitate manual work or as tools subject to human critique. For example, instead of manually identifying topics from scratch, a human could validate and refine the topic list generated by TopicGPT, as well as the assignments it produces. This approach substantially reduces effort while maintaining reliability.

## 4 Related work

Bacinger et al. present a semi-automated system supporting the search and screening phases of literature reviews. It automates the retrieval of articles from multiple sources, helps define search terms, and uses machine learning models to identify relevant papers. It also supports curating and exporting the final set of papers [2]. While Bacinger et al.'s tool uses database searches, ProfOlaf uses snowballing, as prior studies show it performs as well as or better than database searches [3, 8]. Moreover, Bacinger et al.'s system does not support data extraction from articles.

Agarwal et al. introduce LitLLM, an LLM-based toolkit for the generation of scientific literature reviews. It automatically generates search keywords from user-provided abstracts, retrieves and re-ranks relevant papers, and produces related work text grounded in these papers through Retrieval-Augmented Generation [1]. Despite its text generation power, LitLLM lacks manual curation or snowballing, unlike ProfOlaf's human-in-the-loop workflow.

He et al. propose PaSa, an LLM-based agent for academic paper search. PaSa automates query generation, retrieves and expands results through citation networks, and uses a selector agent to evaluate relevance, thereby enabling comprehensive and accurate literature retrieval [7]. The authors' work emphasizes automated retrieval and screening but does not allow manual curation, whereas ProfOlaf balances automation with the researcher's control.

Li et al. present ChatCite, a tool that automates literature summarization by extracting key elements from papers, generating comparative summaries through an iterative reflective process,

and evaluating the results with a novel automatic metric called G-score [11]. Unlike ProfOlaf, which covers the review cycle from the search to the data extraction phase, ChatCite focuses exclusively on summary generation and is therefore complementary.

## 5 Conclusion

ProfOlaf addresses key challenges in systematic reviews by combining iterative snowballing with LLM-assisted analysis, striking a balance between automation and human oversight. By improving efficiency, rigor, and reproducibility, it enables researchers to conduct higher-quality reviews with reduced effort. Given the rapidly growing volume of research in software engineering, ProfOlaf can be valuable in helping SE researchers keep pace with the field.

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