



Collaborative Literature Search System: An Intelligence Amplification Method for Systematic Literature Search

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Abstract. In this paper, we present a method for systematic literature search based on the symbiotic partnership between the human researcher and intelligent agents. Using intelligence amplification, we leverage the calculation power of computers to quickly and thoroughly extract data, calculate measures, and visualize relationships between scientific documents with the ability of domain experts to perform qualitative analysis and creative reasoning. Thus, we create a foundation for a collaborative literature search system (CLSS) intended to aid researchers in performing literature reviews, especially for interdisciplinary and evolving fields of science for which keyword-based literature searches result in large collections of documents beyond humans' ability to process or the extensive use of filters to narrow the search output risks omitting relevant works. Within this article, we propose a method for CLSS and demonstrate its use on a concrete example of a literature search for a review of the literature on human-machine symbiosis.

Keywords: Intelligence amplification · Method
Collaborative literature search system · Human-machine symbiosis
Design science research

1 Introduction

Literature reviews are an essential part of the evolution of scientific knowledge as they summarize the state of the art, uncover knowledge gaps, and provide guidance for further research endeavors. By conducting a systematic literature review (SLR), researchers seek to systematically search, evaluate, and synthesize research evidence. This process remains predominantly “manual” because—for now—only human beings can review and evaluate the scientific material required by high-quality literature reviews. Consequently, this creates a limitation in the volume of scientific publications that can be processed.

Nevertheless, there are an ever-increasing number of research publications, which holds great potential for the synthesis of insightful knowledge. However, as the results

and quality of a literature review essentially depend on the literature selected, it becomes a complex and time-consuming challenge to identify the relevant publications in the jumble of documents that can amass in a literature search. This is reinforced by the fact that many research disciplines have become more interdisciplinary [1, 2], intertwining into an increasing variety of research communities. In this context, students and novice researchers may particularly struggle to get a clear overview of the existing research streams and underlying literature. A second challenge that comes with this problem is the use of different terms for similar or identical concepts.

With advancements in business intelligence, data mining, visualization, and technical computational power, it seems obvious that information technology can provide useful support for the literature-search task in the literature-review process. Indeed, there are a variety of tools that support or automate manual literature search conducted by humans (e.g., systematic literature search systems) [3]. However, since literature search is also a creative process to a certain extent (e.g., the identification of a starting point) [3], full automation is difficult to achieve [4]. Thus, the resulting design objective of this paper is to construct a method that combines the strengths of human and computers for conducting literature search for literature reviews.

Following the design science research (DSR) approach, which deals with the development of novel artifacts that solve or improve real-world problems [5–7], this paper makes two contributions to the DSR body of knowledge [5, 8]. First, we propose a method for conducting literature search while doing SLRs based on the collaboration between two entities: the human and the machine. Recognizing that each entity has different strengths and weaknesses, we propose a process that relies on the strengths of each entity to complement the weaknesses of the other such that the overall result is greater than what each entity could achieve on its own. Our approach is based on the idea of intelligence amplification—that is, the symbiotic interaction between human and machine [9] through which the processing power of computers to visualize and calculate measures in document networks and humans’ creativity and visual perception for reasoning are merged to form a symbiotic entity, enabling superior literature search, exploration, and result selection. We refer to this class of literature search systems as *collaborative literature search systems (CLSS)*. Second, besides an abstract method description for CLSS, we present a prototypical instantiation of the method and demonstrate its applicability in practical case, which serves as validation for the proposed method.

The structure of the paper essentially follows the DSR process model from [7]. The problem definition is covered in the introduction (Sect. 1) and throughout the provided background knowledge on literature search in SLRs and human-machine symbiosis (Sect. 2). In Sect. 3, we describe the collaborative literature search method, which includes the objectives of the artifact and the essential components of its design and development. The demonstration and evaluation of the artifact is given in Sect. 4. Section 5 compares our solution with other approaches proposed in related work, and Sect. 6 provides some concluding remarks and pointers for future work.

2 Background

2.1 Literature Search in Literature Reviews

Literature reviews are an essential part of every research project [1]. They mainly comprise the following steps: (1) collecting data (search and select literature); (2) structuring, synthesizing, exploring, and analyzing data (summarize evidence); and (3) presenting results (disseminate results) [10].

The notable challenges in literature reviews include the increasing number of articles, information overload, increasing complexity, and pressure to obtain comprehensive coverage of article collections. Locating and identifying relevant documents are key factors in literature reviews. To support literature reviewers (from here on called reviewers), the academic literature provides a rich body of approaches and guidelines [11], emphasizing different literature-search strategies, such as keyword-based search, backward search, and forward search [1, 12]. There is also a broad range of software tools that support or automate the different phases of the literature-reviews process, including systematic literature search systems [3] and recommender systems aiding the identification of further potential citations [13]. Additionally, there are various approaches and techniques that help researchers structure and analyze documents and their contents, such as topic modeling [14], discipline structuring [15], authorship analysis [16], and knowledge diffusion [17], as well as tools to support the literature analysis [18]—for example, visualizing connections between research articles [19]. Nevertheless, although there are solutions for partial problems in the literature-review process, there is a lack of support for tasks that require human creativity (e.g., the so-called cold-start problem of determining a starting point for literature search), especially when the reviewer does not have in-depth knowledge of the field at hand.

2.2 Intelligence Amplification/Human-Machine Symbiosis

While the predominant system design approach is to automate as much as possible and reduce human intervention to increase efficiency [20], others recognize that humans play an important role in contexts that do not allow full automation [21]. For example, humans are better in creative tasks whereas machines are better in computational tasks [22].

The idea of intelligence amplification or human-machine symbiosis can be traced back to the work of Licklider [9] and is central to the vision put forward by the new smart industry paradigm. Unlike in artificial intelligence (AI), the goal of which is to create an artificial decision maker that mimics the human brain, intelligence amplification (IA) is based on the “human-in-the-loop” approach. In IA, both the human and the AI agent form a symbiotic partnership, in which the human entity defines strategy, oversees the AI agent, and corrects its decisions when needed, and the AI agent executes routine tasks according to the strategy. In [9], Licklider makes a fundamental observation: the time it takes a human to make a decision, regardless of the complexity, is negligible compared to the time required to complete the steps preceding the decision itself as well as the time for execution afterward.

To the best of our knowledge, no work exists that takes a symbiotic human-machine approach for designing a solution to support literature search and knowledge

extraction. The need for such a method becomes especially evident in evolving and interdisciplinary fields for which the number of documents retrieved through rigorous keyword searches is beyond human processing abilities or for which the extensive use of filters to narrow the output risks omitting relevant concepts and publications coming from different scientific fields possibly using different yet semantically similar terminology. Machines can process huge data volumes quickly but lack the ability to reason and draw conclusions beyond the programmed parameters. Humans (experts in their fields) can evaluate any kind of material, but the volume they can handle is limited. Therefore, an ideal symbiotic partnership should be organized in such a way that the human sets the parameters the machine uses to mine the available scientific information and filter more relevant documents using basic reasoning, which will in turn allow the human to focus on the most important documents and complete the evaluation.

This paper addresses this shortcoming by proposing a CLSS that provides effective automation support through metadata extraction. The proposed method enables researchers to conduct faster and more thorough literature reviews as well as detect, extract, and connect interdisciplinary knowledge from different scientific fields.

3 Method

3.1 Seed-Based Search

A literature-search approach in SLR starts with the researcher selecting keywords and using them to search bibliographic databases for relevant scientific articles. This approach often returns a large number of articles that match the search criteria, so understanding their mutual dependencies becomes challenging. Therefore, we propose an alternative approach that emphasizes the relationships between documents based on their shared citations and references. In our seed-based approach, the idea is to start with an initial set of relevant documents (which we call seeds) and query bibliographic databases to conduct forward and backward literature search corresponding to a citation analysis. This initial set of articles can be, for example, the result of ad hoc keyword-based searches or recommended articles by colleagues. The result is transformed into a directed graph, in which each document is represented as a node and every citation and every reference becomes an edge. Through graph analysis, it is possible to identify the nodes that are most related (and possibly relevant) to the initial seed(s). The reviewer then performs a qualitative analysis of those documents. Each document that is identified as relevant for the literature review is added to the seed set and the process is repeated until a stop-criterion is achieved—that is, no additional seeds are discovered or a maximum search depth is achieved.

We illustrate this process with the following example (illustrated in Fig. 1). We assume that for a specific scientific field, the reviewer is familiar with three articles: A, B, and C. Two articles (A and C) are deemed to be influential and selected as seeds. Therefore, the initial graph contains two nodes. For this given example, article A is referenced by B and D, and article C is cited by B. After conducting the forward search for the next depth, articles B and D are added to the graph. Since B was already known

to the reviewer, it is excluded from further consideration. However, this process also raises the reviewer's awareness about article D, which is related to the two already known and relevant articles.

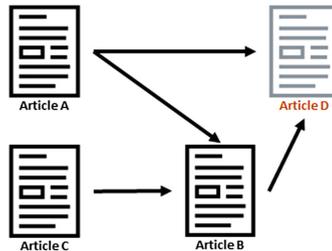


Fig. 1. Illustration of the discovery of the new articles through seed-based search

3.2 The Process

The search process contains four consecutive steps. In Step 1, the search parameters are determined. Expanding the document graph through forward and backward search of bibliographic databases is done in Step 2. In Step 3, found articles are analyzed, and the results are visualized in a way that allows quick understanding by the human. This step also includes highlighting potentially important articles based on the network analysis. Step 4 includes the examination of the extended list of articles and comparison with the current list of articles to determine if new search seeds can be identified. If there are new seeds, the process returns to Step 2 and is repeated until no new seed articles are found. Finally, articles are filtered (e.g., by publication year) to produce a final collection of articles that is manageable by the human. Afterward, the reviewer analyzes all articles in the list and moves on to the review. Figure 2 illustrates the steps of the intelligence amplification literature search and, most importantly, how they fit within the classical literature-review process. The proposed method replaces and automates search and acquisition and enhances some analysis and interpretation activities.

Since our method is based on the human-in-the-loop approach, in Step 1, human reviewers define the search criteria. As we base our search on citation analysis initiated by the given seeds, this step requires the reviewers to use their experience to identify the most relevant seed articles (*sa*) concerning the scientific field under review. To reduce unavoidable human bias, we recommend that more than one reviewer be involved in this step and that each creates a separate initial list of possible seeds, which will result in a consolidated collection of articles.

Step 2 and Step 3 are delegated to the machine. First, the intelligent agent queries bibliographic databases and performs forward and backward search based on the selected seeds and the depth set in Step 1. Forward search extracts all articles that cite the given seeds, and the backward search extracts all articles referenced in the seeds. Optionally, this search can be limited in depth and constrained with keywords to prevent it from exploding into literature retrieval from non-related scientific fields. The extraction is expected to generate potentially large lists of documents, which are not

suitable for human evaluation. To address this issue, the intelligent agent is required to transform the list into a directed graph and cluster the nodes (i.e., documents) according to their relationships. This is done in Step 3. In Step 4, the reviewers examine the graph structure, but prior to that, additional visual cues need to be implemented to enable humans to quickly distinguish documents’ publication year, number of connections, and relationship to the specific scientific field. One option is the use of visual markers to highlight potentially outstanding articles. These are typically so-called *bridging articles*—namely, documents that connect different scientific fields. Often, such papers lead to a *paradigm shift* and give rise to what Kuhn [23] calls a *scientific revolution* that significantly impacts a certain scientific field. Intelligent agents do not have humans’ expertise to accurately determine such articles, yet machines can analyze the graph structure and provide visual cues for these “event nodes” (i.e., nodes representing paradigm-shifting articles) if certain conditions are met. Typically, these have a high number of citations and are the centers of a node cluster. We suggest that reviewers set a threshold (t) value, which is used to filter nodes by the number of different clusters each node is connected to.

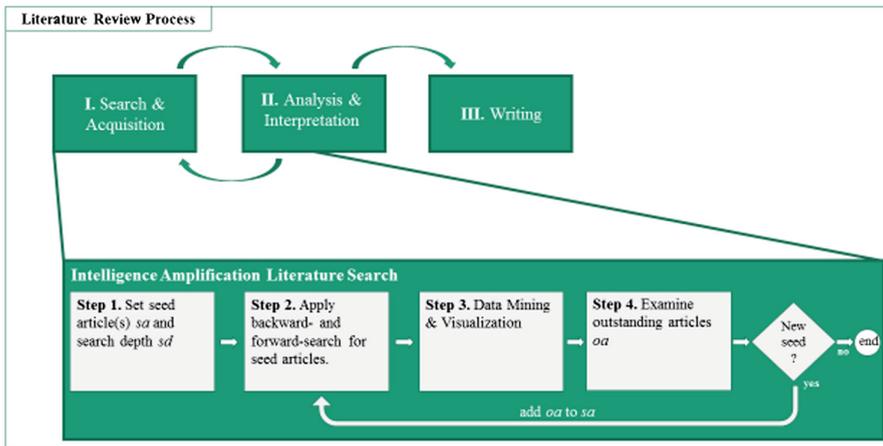


Fig. 2. Literature-review process and enhancement with intelligence amplification literature search

Aided by the visual cues and metadata extraction, in Step 4, the reviewers inspect the generated graph structure. Through the first level of publication filtering—by name and by abstract—the reviewers orient themselves to their potential areas of interest. As the documents are grouped within clusters, the reviewers can quickly decide to exclude unrelated document groups by inspecting cluster cores and the connected articles. By analyzing both highlighted articles and those they discovered by exploiting the graph structure, the reviewers can identify new seeds, and the process can be repeated from Step 2. If no new outstanding articles are found and/or the graph structure has converged toward a stable form, the process is finished, and all nodes in the structure

become candidates for the literature review. At the end, the reviewers may opt to apply additional filters (e.g., publication year, connection strength between the article and the seeds) if the number of articles is still too high for human processing. Following that, the process provides the input for the next step of the literature-review process. The reviewers investigate each document thoroughly and formulate answers to their initial research question.

4 Demonstration and Evaluation

An essential component of every DSR project is an evaluation that rigorously demonstrates that the proposed solution addresses the stated problem [6]. The DSR literature proposes several approaches to plan evaluation strategies [24].

To demonstrate the effectiveness of our proposed method, we opted for a demonstration of the method by implementing a software tool that performs the machine's tasks. Like other studies in the field of scientometrics (e.g. [19, 25]), we demonstrate the method by providing details on an illustrative scenario, as described below [24].

The tool connects to the Scopus database via the official application programming interface (API), conducts the forward and backward search, and extracts the citation graph. The tool is used for Step 2 and Step 3 (see Sect. 3.2). The pseudo code for the document extraction is given in Fig. 3.

```

extract (seed_id, search_depth, keyword_list)
  set history_list, open_list to empty
  initialize Graph
  copy seed_id to open_list
  set depth to 0
  while depth < search_depth
    for each node in open_list
      neighbors = CALL_ADJECENT_API_SEARCH(node)
      append neighbors to adjacent_nodes
      for each n in neighbors
        if (KEYWORDS(n) in keyword_list) and (NOT(n in history_list))
          Graph.add_edge (node, n)
          else delete n from adjacent_nodes
      append open_list to history_list
      copy adjacent_nodes to open_list
      set adjacent_nodes to empty
      depth = depth + 1
  return Graph

```

Fig. 3. Pseudo code for document extraction and graph generation via a database-specific API

Figure 4 shows the graph resulting from the search for two arbitrary seeds. Figure 4(a) shows the transformation of the extracted documents into nodes on the directed graph and their references and citations as graph edges. In Fig. 4(b), nodes have been clustered to make the structure more comprehensible for the human researcher. In Fig. 4(c), we use arrows to point to the visual cues given by the

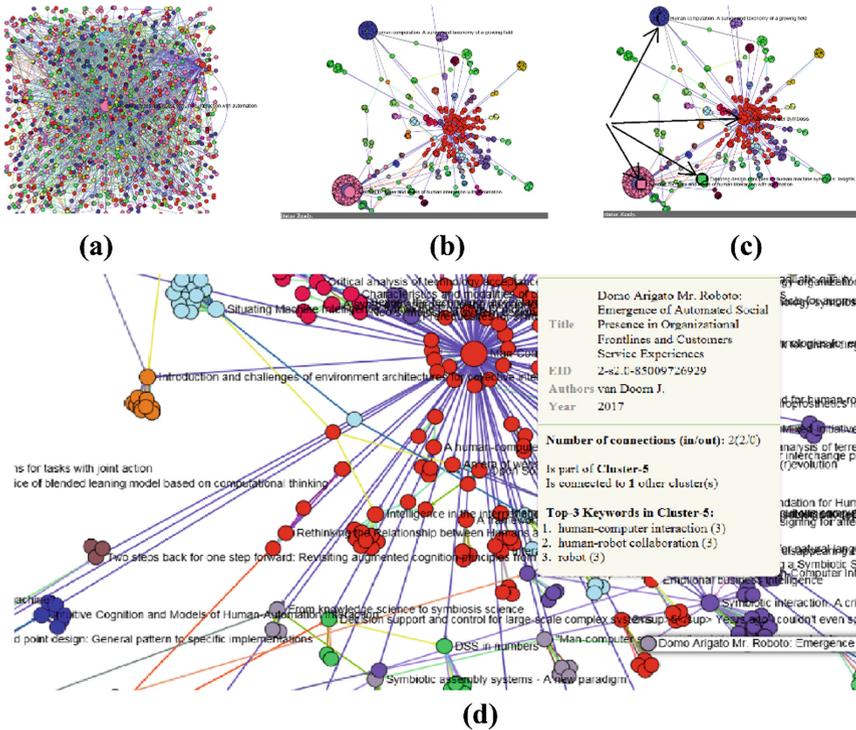


Fig. 4. Visualizing citation network as a directed graph with metadata

algorithm to indicate outstanding articles (*oa*), which are rendered as large squares instead of circles. Finally, in Fig. 4(d), we show how to zoom into the node structure and obtain specific document-related information.

We selected the literature from the field of human-machine symbiosis because we believe it is a good candidate to demonstrate our solution and evaluation as it (1) spans fields from theoretical computer science to practical robotics application and (2) is challenging for humans to fully process as a traditional keyword-based search returns well beyond thousands of articles. For simplicity, we decided to use a single seed for the initial search, and because Licklider is considered the most influential author for the origins of human-computer symbiosis, we used [9] (MCS) as the initial seed (cf. Step 1 in Sect. 3.2). In the following, we briefly describe the results of our execution of the defined method steps. Due to page constraints, each seed is coded using an acronym, while the full title, author(s), and publication year for each document is given in Table 1.

We used the Scopus database, set the algorithm to the maximum search depth of 2, and added a filter to exclude papers that do not have keywords related to human-machine symbiosis. The first iteration of Step 2 returned 753 documents. The analysis of these documents was done through the symbiotic partnership between us (i.e., the human reviewers) and the machine. The machine used a clustering algorithm

Table 1. Acronyms used for labeling event nodes

Acronym	Authors	Title	Year
MCS	Licklider	Man-computer symbiosis	1960
HC	Quinn and Bederson	Human computation: a survey and taxonomy of a growing field	2011
SI	Jacucci et al.	Symbiotic interaction: a critical definition and comparison to other human-computer paradigms	2014
EDP	Döppner et al.	Exploring Design Principles for Human-Machine Symbiosis: Insights from Constructing an Air Transportation Logistics Artifact	2016
FPS2MCS	Guo et al.	From participatory sensing to Mobile Crowd Sensing	2014
MCSC	Guo et al.	Mobile Crowd Sensing and Computing: The review of an emerging human-powered sensing paradigm	2015
DC	Hollan et al.	Distributed Cognition: Toward a New Foundation for Human-Computer Interaction Research	2000
TI	Hornecker and Buur	Getting a grip on tangible interaction: A framework on physical space and social interaction	2006
AE	Kirsh	Adapting the environment instead of oneself	1996
IEPDL	Fast and Sedig	Interaction and the epistemic potential of digital libraries	2010
VABD	Ren et al.	Visual analytics towards big data	2014
MIwCEI	Smart	Situating Machine Intelligence Within the Cognitive Ecology of the Internet	2017
DC#V	Liu et al.	Distributed cognition as a theoretical framework for information visualization	2008

for the citation network analysis, which was combined with the human-defined threshold parameters to render the graph and to highlight the potentially most relevant articles in the structure. Detailed information about the input and output values per iteration, including suggested event nodes by the machine in response to the human-defined threshold t , is given in Table 2. Figure 5(a) shows the zoomed-out directed graph—that is, the result of Iteration 1—which contains information on 753 extracted articles and their correlation. We then explored the graph, focusing on the suggested event nodes.

As Iteration 1 had a few clusters, only low threshold parameters ($t = 3$ and $t = 4$) yielded outstanding articles (*oa*) beside the initial seed. We then inspected each node, checked the relevance of the title and abstract, and finally evaluated the content of the full article. We found SI [26] and HC [27] to be quite relevant to the search and good candidates for the next seed. HC has more citations, so more edges connect it with other nodes, and it also resides closer to the center of the graph. However, because we concluded that HC is a taxonomy paper from its content, we gave preference to SI as the next seed. In Fig. 5(b), we show how the tool provides analytical assistance to researchers by showing metadata about the highlighted node that can be inspected by humans. The view is zoomed in and rotated to show the connection between the new

potential seed SI and the original seed MCS. From the tool, we obtained additional info about the node and its cluster: document title, author, number of connections, most common keywords, number of citations, and publication year.

Iteration 2 started with two seeds: MCS and SI. All other parameters remained unchanged. This resulted in 1,193 related articles. Exploring the structure with alternating event thresholds, two additional nodes were highlighted as potential paradigm shifts. These nodes are HC, which was already discovered in Iteration 1, and the new node: DC [28]. Based on the content of DC, we selected it as the most relevant node and added it to the seed list. Iteration 3 increased the node number to 2,427. Again, visual inspection of the results, together with experimenting with different thresholds, yielded three more seeds: HC, TI [29], and AE [30]. Based on the content, we found that these seeds are relevant, yet we noticed that their disciplinary focus is moving away from the core of human-machine symbiosis. We still proceeded to the Iteration 4 but reduced the search depth to 1, ultimately obtaining 2,427 nodes. As the graph structure and suggested event nodes remained similar to the previous iteration, we concluded that the structure converged toward a stable form and stopped the search. Figure 5(d) shows the zoomed-out view of the graph after concluding this phase.

Table 2. Input and output parameters for each iteration with suggested seeds per threshold level

		Iteration				
		1	2	3	4	<i>filter</i>
Input	Seed	MCS	MCS, SI	MCS, SI, DC	MCS, SI, DC, HC, TI, AE	MCS, SI, DC, HC, TI, AE
	Search depth	2	2	2	1	n/a
	Database	Scopus				
	Keywords filter	Intelligence amplification, Intelligence augmentation, Human-machine symbiosis, Human-computer symbiosis, Human-machine collaboration, Human-machine cooperation				
Output	No. nodes (documents)	753	1193	2427	2427	323
	No. edges (ref. + cit.)	842	1308	2847	2848	335
	No. clusters	38	30	48	52	6
Event nodes	t = 3	<i>MCS, SI</i> , HC, EDP, FPS2MCS, MCSC	<i>MCS, SI, DC</i> , HC	<i>MCS, SI, DC, HC, TI, AE</i> , IEPDL, VABD, MlwCEI, DcfIV, (+11)	<i>MCS, SI, DC, HC, TI, AE</i> , IEPDL, VABD, MlwCEI, DcfIV, (+14)	n/a
	t = 4	<i>MCS</i> , HC	<i>MCS, SI, DC</i> , HC	<i>MCS, SI, DC, HC, TI, AE</i> , IEPDL, VABD, MlwCEI, DcfIV	<i>MCS, SI, DC, HC, TI, AE</i> , IEPDL, VABD, MlwCEI, DcfIV	n/a
	t = 5	<i>MCS</i>	<i>MCS, SI</i>	<i>MCS, SI, DC, HC, TI, AE</i> , IEPDL	<i>MCS, SI, DC, HC, TI, AE</i> , IEPDL, VABD	n/a
	t = 6	<i>MCS</i>	<i>MCS, SI</i>	<i>MCS, SI, DC, HC, TI, AE</i>	<i>MCS, SI, DC, HC, TI, AE</i> , IEPDL	n/a

The final phase involved using the symbiotic human-machine partnership and narrowing down the set of extracted articles to one that is manageable by the human for full qualitative analysis. We used the tool to identify and select articles connected to the extracted seeds: MCS, SI, DC, HC, TI, and AE. We chose to keep only the documents

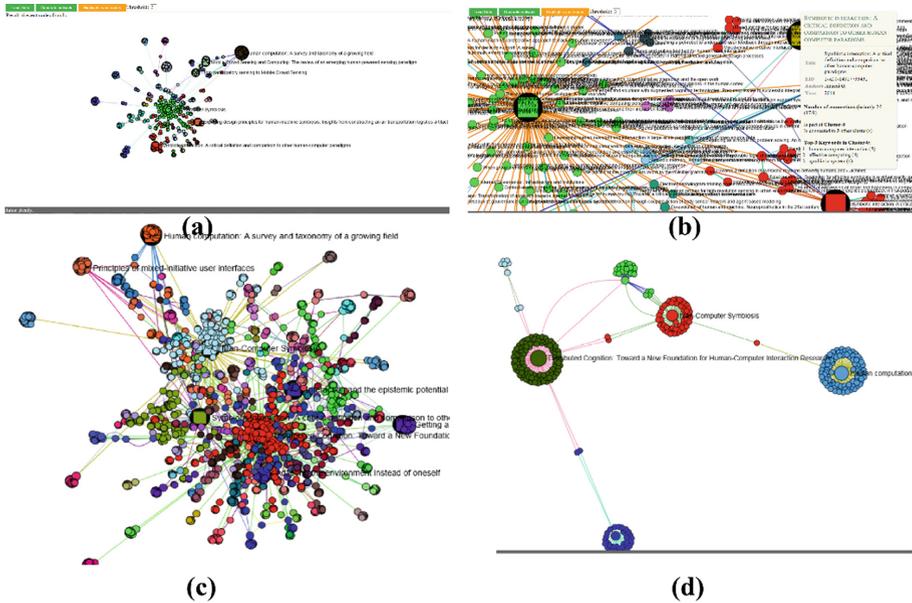


Fig. 5. Visualization of document extraction and analysis for “man-computer symbiosis” seed published within the last five years and added the criterion that each must be connected to at least one seed. This gave us the structure shown in Fig. 5(d), which contains 323 documents. Following that, human expertise was required to assess the relevance of each article based on the title and abstract and to determine the final consolidated list.

5 Related Work

The research from the field of scientometrics is rich with publications focusing on measuring the impact of scientific publications [31]. Many research groups have investigated literature search and have produced software packages for mapping scientific field(s). For example, CiteSpace [25] provides keyword extraction, landscape, and timeline view from a variety of sources, such as Web of Science (WoS), Scopus, and PubMed. VosViewer [19] also uses data from WoS, Scopus, and PubMed and incorporates clustering and non-linear programming techniques to process and visualize the data. However, data extraction is not included in the process as these tools assume that the human reviewer obtains all the data and loads in one go, thus limiting the potential for sequential discovery.

Due to its powerful analysis features, easy and effective user interface, and ability to use data obtained from Scopus, we decided to use VosViewer [19] to demonstrate the execution of the process described in Sect. 4 based on the search spawning from Licklider’s publication on man-computer symbiosis [9]. Thus, we explored the literature through search queries and extracted publication lists using Scopus’ web interface.

The initial Scopus search using the query “TITLE-ABS-KEY (man-computer AND symbiosis)” returned 14 results, from which no significant correlation was found. Therefore, we obtained Scopus-specific unique paper identifiers (EID) for [9] (2-s2.0-84936949820) and used it to redefine the query, extracting MCS and all documents citing it. By running the following query, we obtained a list of 456 articles and exported it in .csv format: “REF (2-s2.0-84936949820) OR EID (2-s2.0-84936949820).” We then loaded this list in VosViewer, choosing the option to create the map based on the bibliographic data. We set the type parameter to citation analysis and set the unit parameter to documents. Finally, we set the minimal number of citations threshold to 0 and included all documents. The result is given in the Fig. 6(a) below.

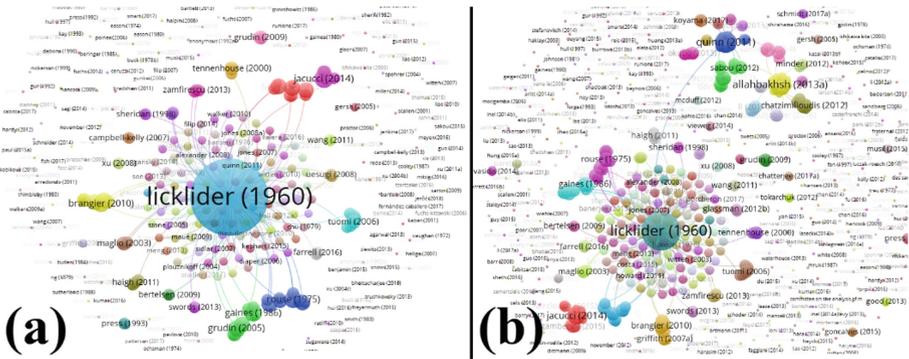


Fig. 6. Visualizing citation network for the man-computer symbiosis literature using VosViewer

Next, we examined the papers in the larger clusters of Fig. 6(a) and selected the publication by Jacucci et al. [26] (tagged as SI in Table 2). The paper HC [27] by Quinn and Bederson is in the list, but because only a few edges are connecting it with other nodes in the graph, it is not easily identifiable by the human. Nevertheless, we decided to include HC and SI in the next iteration to increase the complexity of the network and create a structure that is easier to compare with the graph we obtained after Iteration 3 and Iteration 4 in Sect. 4. We manually extracted all seed papers’ unique EIDs and ran a new query in Scopus’ browser interface: “REF (2-s2.0-84936949820) OR EID (2-s2.0-84936949820) OR REF (2-s2.0-84917733431) OR EID (2-s2.0-84917733431) OR REF (2-s2.0-79958083139) OR EID (2-s2.0-79958083139).” This search resulted in 825 papers, which VosViewer generated into the graph shown in Fig. 6(b).

After we examined new highlighted clusters and determined they were not relevant for further investigation, the search did not acquire new seeds and the process stopped. Thus, this process resulted in a list of 825 papers and no clear indication of how to proceed further with paper selection. These results contrasts with the more than 2,000 articles obtained through our CLSS after Iterations 3 and 4.

However, it should be noted that the capabilities of VosViewer exceed the visualization functionality included in our tool by far. The main advantage of our solution is thus not related to visualization per se but rather to the strategy we propose for

searching and obtaining the data itself. The fact is that our method includes custom machine-assisted extraction, which can perform both forward and backward search and in larger depths, provides more data. Thus, it is possible for our tool to discover more clusters, and within those clusters, it can find outstanding articles that can be used as further seeds. As both VosViewer and CiteSpace are designed for data extracted manually by humans from pre-defined sources, they are constrained by that input. With an increasing number of seeds, this search process becomes more complex and creates more fatigue, ultimately causing the human component to be the bottleneck. Nevertheless, if VosViewer and CiteSpace enable custom data to be loaded, we expect that better (visualization) results could be obtained using our proposed extraction process and method together with the analytical functionality of those tools.

6 Discussion and Future Work

In this paper, we proposed a method for conducting collaborative literature search for SLRs using a symbiotic partnership between humans and machines. We showed that our method based on the principles of seed-based search and intelligence amplification (i.e., where machines augment the capabilities of human domain experts) has potential as a complementary approach to traditional search. Finally, we illustrated the method in a CLSS and demonstrated its application for obtaining an article list for a literature review in the field of human-machine symbiosis.

With our CLSS, we aim to provide efficient assistance for SLRs, particularly in interdisciplinary research domains as well as evolving scientific fields that typically use different terminology and keywords for similar concepts. When the literature review requires the processing of large amounts of publications beyond human capabilities, CLSS can be used by researchers to quickly identify potentially important publications. Through an interactive search of the generated directed graph, researchers can influence how the graph structure evolves as new seeds and paradigm shifts are identified. CLSS enables researchers to maintain a helicopter view of a large set of articles and aims at improving their ability to conduct SLR in an ever-increasing pool of scientific information while reducing the risk of potentially missing essential concepts and bridging articles.

In this paper, we demonstrated the first application of our proposed method and implemented an algorithm to retrieve important articles within a document collection. As we obtained data from a single bibliographic database, future work should focus on improving the scalability of the CLSS, examine further identification approaches, and expand literature sources. This would also strengthen the rigor required for SLR. In terms of performance, there is also room for improvement by adjusting the data mining (clustering) algorithms to enable real-time big data processing. This, together with improving the interface of the frontend component, would make interactive real-time content analysis possible, enabling researchers to dynamically add and remove seeds while exploring the literature landscape [32].

Gathering data about the usage of the CLSS, it might be interesting to analyze typical literature-exploration trajectories and train models that allow the machine part to recommend efficient trajectories (stronger assistance power). Shifting from a submissive

role in the collaborative relationship, the system can become more powerful to guide the reviewer through the literature-search process. Because the focus of the proposed method is on the literature-search phase of SLR in this paper, it might be interesting for further research to use the lens of human-machine symbiosis and investigate its suitability for the design of IT support for the subsequent SLR phases.

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