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Computational Literature Reviews: Method, Algorithms, and Roadmap

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Abstract

The substantial volume, continued growth, and resulting complexity of the scientific literature not only increases the need for systematic, replicable, and rigorous literature reviews, but also highlights the natural limits of human researchers' information processing capabilities. In search of a solution to this dilemma, computational techniques are beginning to support human researchers in synthesizing large bodies of literature. However, actionable methodological guidance on how to design, conduct, and document such computationally augmented literature reviews is lacking to date. We respond by introducing and defining *computational literature reviews* (CLRs) as a new review method and put forward a six-step roadmap, covering the CLR process from identifying the review objectives to selecting algorithms and reporting findings. We make the CLR method accessible to novice and expert users alike by identifying critical design decisions and typical challenges for each step and provide practical guidelines for tailoring the CLR method to four conceptual review goals. As such, we present CLRs as a literature review method where the choice, design, and implementation of a CLR are guided by specific review objectives, methodological capabilities, and resource constraints of the human researcher.

Keywords

computational literature reviews, CLR method, systematic reviews, text mining, machine learning, artificial intelligence

> Where is the knowledge we have lost in information?
>
> —T. S. Eliot, *The Rock*

Introduction

The scientific knowledge available to humankind has increased exponentially since the beginning of the 20th century (Rosenthal & DiMatteo, 2001). The first academic journal appeared in 1665, and

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the cumulative corpus of all peer-reviewed scholarly articles in existence today exceeds 50 million texts (Jinha, 2010). Approximately 2.5 million new articles are added to this corpus per annum from over 20,000 peer-reviewed academic journals (Ware & Mabe, 2015). To consolidate this wealth of knowledge for research, practice, and policy, systematic literature reviews are increasingly important for researchers of all levels of experience. Specifically, systematic literature reviews help develop an accumulated body of knowledge (Mulrow, 1994), direct future research endeavors (Webster & Watson, 2002), identify emerging trends in scholarly debates (Neely et al., 2010), and support evidence-based decision making by locating, appraising, and synthesizing critical text corpora (Briner et al., 2009).

The substantial volume, continued growth, and resulting complexity of the scientific literature available today not only increases the need for systematic, replicable, and rigorous literature reviews, but also makes it increasingly resource-intensive to conduct them (Badger et al., 2000). Given the natural limits of human researchers' information-processing capabilities, extracting critical evidence (Briner et al., 2009), detecting subtle cues (Denyer & Tranfield, 2009), and recognizing latent patterns (Simon, 1990) from large and complex scientific text corpora will, at best, become more costly and lengthy and, at worst, become infeasible (Cropanzano, 2009). The current academic discourse, as exemplified in this feature topic of *Organizational Research Methods*, explicitly recognizes this dilemma and calls for new methodological approaches to address this challenge.

One promising path to overcome the limitations of traditional, manual literature reviews is to incorporate computational methods. This avenue has the potential to combine the respective strengths of human researchers' insights and judgment with computers' speed and efficiency when synthesizing large bodies of text (Paré et al., 2016). To understand the benefits of this approach, consider the following explanation of best practices for conducting *any* systematic literature review:

> Systematic reviews are characterized by a methodical and replicable methodology and presentation. They involve a comprehensive search to locate all relevant published and unpublished work on a subject; a systematic integration of search results; and a critique of the extent, nature, and quality of evidence in relation to a particular research question. The best reviews synthesize studies to draw broad theoretical conclusions about what a literature means, linking theory to evidence and evidence to theory. (Siddaway et al., 2019, p. 1)

Computational approaches to conducting systematic literature reviews are aligned with the best practices described by Siddaway et al. (2019) and are useful for handling large bodies of published and unpublished texts and uncovering previously unseen connections among documents and their content. We recognize that the unique ability of human researchers to compile and connect information in new ways is at the heart of the critical task of synthesis that is required when conducting systematic literature reviews. Our study highlights the added value that computational approaches may offer in helping people discover new knowledge or, in some cases, rediscover existing knowledge before carefully extracting meaning. As a case in point, early attempts in organizational research have begun to leverage techniques from text mining (Feldman & Sanger, 2007) and natural language processing (Cambria & White, 2014) to augment individual human tasks needed to perform systematic literature reviews.

This includes recent in-depth analyses of specific *research topics* such as disruptive innovation (Hopp et al., 2018), open innovation (Randhawa et al., 2016), or technology acceptance models (Mortenson & Vidgen, 2016), as well as broad analyses of entire *academic journals* like the *Strategic Management Journal* (Antons et al., 2019) or *Decision Sciences* (Chae & Olson, 2018), and overarching *scientific fields* (e.g., field of system dynamics; Kunc et al., 2018). These examples demonstrate the variety of scholarly settings in which computational methods can increase the *scale* of systematic literature reviews, compared to manual approaches. In addition, the application of computational methods also increases the *scope* of systematic literature reviews by identifying, extracting, and ultimately synthesizing knowledge held within and across academic disciplines that may otherwise be infeasible or inaccessible by manual analysis (Boyd-Graber et al., 2017).

For example, computational methods can isolate the vocabulary used within specific fields of study (Steyvers et al., 2004), examine how distinct scientific fields interrelate and influence each other (Paul & Girju, 2009), or map the ongoing evolution of scientific research themes and citations (He et al., 2009). For instance, Antons et al. (2016) produce an array of maps that visually depict the topic structure of the *Journal of Product Innovation Management* and characterize hot, cold, and wallflower topics. Editors and reviewers may benefit from these maps by filling in the gaps between topics, focusing on hot topics, reviving cold topics, and energizing wallflower topics, thus heightening the scholarly impact of syntheses generated through computational methods.

The efforts highlighted above demonstrate the potential of computational approaches for conducting systematic literature reviews vis-à-vis traditional manual approaches. However, if computational approaches are to emerge as a widely accessible and rigorous method for conducting systematic literature reviews, comprehensive and actionable methodological guidance is needed. Importantly, such guidance is still missing, as extant attempts to guide future researchers adopted a narrow technical focus on individual text mining algorithms such as topic modeling (e.g., Schmiedel et al., 2019), their requirements for text preprocessing (e.g., Rüdiger et al., 2017), or programming languages (e.g., Hornik & Grün, 2011)—all without direct reference to the specificities of systematic literature reviews. Key methodological questions therefore remain unanswered: What are the defining characteristics of this emerging review method? What are its constitutive process steps? How can computational literature reviews be tailored to the review objectives pursued? What are the most suitable classes of algorithms available to date? How can algorithms and researchers interact to combine the best of artificial and human intelligence? What are the limitations of computational approaches, and how can they be overcome? Addressing these questions is essential for both novice and experienced researchers who currently face considerable adoption barriers and methodological ambiguity when designing and executing computational literature reviews. It is equally relevant for editors, reviewers, and readers of computational literature reviews, who struggle to assess their merits.

We respond to the important and unaddressed need for methodological guidance and contribute by introducing and explaining *computational literature reviews* (CLRs), as a new rigorous literature review method. Even though traditional meta-analyses, bibliometric analyses, and even manual literature reviews (MLRs) are often supported by software, CLRs go an important step further in that they leverage computational algorithms for text mining and machine learning to support the analysis of the *content* (rather than effect sizes or meta-information) of the text corpus to be reviewed. CLRs also differ from traditional MLRs, with algorithms automatically performing essential review tasks without direct human input. As such, they are fully scalable and real-time capable with automatic updates performed whenever new scientific articles become available. This enables researchers, for the first time, to review the content of even the largest and most rapidly evolving bodies of scientific literature in a rigorous, efficient, and timely fashion. We define the CLR method as

> a structured process intended to augment human researchers' information processing capabilities through the use of machine learning algorithms that help analyze the content of a comprehensive text corpus in a specific knowledge domain (e.g., a research topic, academic journal, or scientific field) in a way that is scalable and real-time capable.

CLRs are designed not to replace the efforts of people in all aspects of conducting systematic literature reviews, but to augment their information processing and analytical capabilities for selected tasks that are particularly time-consuming, resource-intensive, or otherwise cost-prohibitive (Raisch & Krakowski, 2020). Following the logic that "human need, skill, creativity and potentiality [should be placed] at the center of the activities of technological systems" (Gill, 1990), we advocate a human-centered approach to CLRs, and "put people before machines" (Cooley, 1996). Specifically, the CLR method tends to *automate* review tasks that are either inefficient or infeasible to perform at scale by human researchers, including laborious tasks such as text preprocessing, where machines have a comparative advantage. In contrast, the CLR method *augments* review tasks that rely on human understanding and creativity by providing machine-generated stimuli. For example, algorithmic outputs and visualizations help human researchers detect patterns in current knowledge and generate meaningful insights for future knowledge discovery. It is this synergistic relationship between computational efficiency and human ingenuity that enables CLR users to review text corpora currently inaccessible with traditional MLR methods, and to focus their scarce temporal, financial, and cognitive resources on generating original insights (Hannigan et al., 2019).

In what follows, we explicate the CLR method by providing a comprehensive six-step roadmap. We cover the entire CLR process from initially identifying the review objectives to be pursued, to selecting appropriate algorithm, and reporting the findings. By identifying critical design decisions and challenges for each step, and by providing practical guidelines, we make CLRs accessible to novice and expert users alike, and present CLRs as a human-centered review method, where the choice, design, and implementation of a CLR are guided by specific review objectives, methodological capabilities, and resource constraints of the human researcher.

Roadmap for Conducting Computational Literature Reviews

Properly designing, implementing, and documenting CLRs enhances not only their rigor and replicability but also their ability to help generate novel and meaningful insights that can guide future research. However, this requires a clear understanding of the design parameters and core tasks of the CLR method. In what follows, we develop a roadmap that highlights six critical process steps. We then explain how to manage the interplay between computational and human activities and provide CLR users with actionable guidelines on how to conduct the CLR method in a way that is rigorous and replicable. Table 1 summarizes this roadmap and the six constitutive steps of the CLR method.

Step 1: Begin With a Conceptual Goal

Every CLR should be guided by, and initially be tailored to, the goal a researcher pursues. This is to ensure that CLRs are more than descriptive summaries of the state of the art (Corley & Gioia, 2011; Short, 2009), but instead initiate or shape a relevant conversation in the field (Cropanzano, 2009). We therefore draw on MacInnis (2011), who delineates four archetypical conceptual goals *any* scholarly inquiry could pursue, and explain how these can be applied and implemented in CLRs. Table 2 provides an overview and examples.

First, the conceptual goal of *explicating* involves expressing and explaining ideas as well as relationships between them, and may be achieved through delineating and summarizing (MacInnis, 2011). Delineating seeks to "unpack" the object of inquiry, and to describe its relationship to other entities. Summarizing, in turn, aims to take stock of—and consolidate—what is already known, provides key insights, but also identifies gaps in knowledge that lead to new research avenues. In the context of a CLR, the goal of explicating may be pursued by providing an overview of the state of a field, to then identify research priorities. Indeed, explicating is a conceptual goal that can be found in numerous CLRs, including the first machine-drafted book by Writer (2019), which summarizes scientific articles in the field of lithium-ion batteries, or Griffiths and Steyvers (2004), who investigate the content of 28,154 abstracts published in the *Proceedings of the National Academy of*

Table 1. The Six-Step Roadmap of the Computational Literature Review (CLR) Method.

Step	Activities	Role of Human	Role of Machine	Rationale	Issues to Consider
1. Begin with a conceptual goal	Explicating: – Delineate by describing the relationship between the object of inquiry and its environment – Summarize by acknowledging what is known about the object of inquiry and identify gaps to advance future research Envisioning: – Identify a new aspect of science (i.e., construct, theory) – Revise an existing aspect of science (i.e., construct, theory) Relating: – Differentiate by decomposing the whole into its constituent parts – Integrate by identifying similarities between previously disconnected parts Debating: – Advocate by providing evidence in favor of a particular stance to be communicated – Refute by undermining confidence in a particular stance to be communicated	– Identify and prioritize pertinent research question(s) to be answered via the CLR – Manage potential discrepancies resulting from multiple or potentially conflicting conceptual goals to be pursued	– Currently available algorithms do not play any role in the CLR at this step	– Ensures that CLR is more than descriptive summary but advances understanding of scientific knowledge domain – Helps to balance efforts on what is directly useful in terms of any new knowledge produced rather than what is technically feasible	– Reviews may have no clear objective, multiple objectives, incompatible or conflicting objectives

(continued)

Table 1. (continued)

Step	Activities	Role of Human	Role of Machine	Rationale	Issues to Consider
2. Operationalize the CLR	– Specify the knowledge domain to be reviewed to pursue the goals proposed in Step 1 above – Compile the text corpus	– Define the appropriate scoping rules or heuristics including timeframe – Screen text corpus for errors, problematic inclusions, or omissions	– Retrieve and download text files from databases, archives, and repositories – Generate scripts to simplify compilation and repeat as needed	– Selects appropriate and relevant databases, archives, and repositories – Synchronizes data sources across time	– Underscoping vs. overscoping the review
3. Choose a computational technique	– Determine suitability of computational technique for review goal and text corpus from Step 2 above – Incorporate computational technique into overall research design	– Determine if computational technique accessible to researcher in terms of technical capabilities and resource constraints – Calibrate algorithm and set parameters	– Currently available algorithms do not play any role in the CLR at this step	– Matches computational techniques to review goals and project characteristics	– Alignment of researchers' relevant experience and algorithm features with review goals and scope
4. Perform the content analysis	– Varies depending on the specific computational technique chosen in Step 3 above, could include the following three activities: (1) preparing the data, (2) calibrating the algorithm, (3) enriching the algorithmic output	– Check for accuracy, plausibility, and compatibility with knowledge domain – Visualize results, solicit additional outputs	– Convert text into machine-readable format – Reduce variability of natural language – Run analytical process and generate standardized outputs	– Systematically captures quantitative metrics associated with observable characteristics of natural language data	– Manage trade-offs: intended review scope vs. computational resources available vs. time required
5. Generate original insights	– Organize and evaluate the meaning of outputs from Step 4 above in context – Conduct plausibility and validity checks, which may require complementary manual analyses – Identify areas for further knowledge discovery	– Interpret algorithmic outputs – Align insights with conceptual goals – Reanalyze selected documents (outliers) manually and/or using alternative computational techniques (repeat Steps 3 and 4 using a subset of the original corpus from Step 2)	– Structure knowledge domain and provide stimuli for human discovery (detect outliers and unusual patterns)	– Compares and contrasts algorithmic outputs with established assumptions, theory, or one's own expectations	– Assess alignment between review goals and output

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Table 1. (continued)

Step	Activities	Role of Human	Role of Machine	Rationale	Issues to Consider
6. Present the findings	– Apply one or more of the following 5 forms of synthesis to present the findings from Step 5 above for scholarly consumption: (i) research agenda; (ii) taxonomy; (iii) alternative models; (iv) meta-analysis; and (v) meta-theory	– Elaborate on future research questions and propositions – Categorize knowledge along relevant dimensions – Illustrate different conceptual frameworks and perspectives – Combine with other analytical techniques to clarify constructs or test boundary conditions – Bridge knowledge domains	– Currently available algorithms do not play any role in the CLR at this step	– Synthesizes the insights obtained from the analyses into useful building blocks for further scholarly inquiry and independent examination	– Evaluation of how the completed CLR process adequately captures and meaningfully critiques the knowledge domain above and beyond prior traditional reviews

Note: As the review process unfolds, researchers may iterate back and forth between steps of the CLR process, especially between Steps 3 to 5.

Table 2. Examples of Early CLRs.

Primary Conceptual Goal	Study	Secondary Conceptual Goal	Corpus and Knowledge Domain(s)	Computational Technique(s)	Findings and Implications
Explicating	Writer (2019)	Relating	53,000 published articles on lithium-ion battery Technology (2015-2018)	Latent Dirichlet allocation (LDA)	First machine-drafted and human-revised book. Demonstrated proof of concept for augmented summarization of scientific articles.
	Lee and Kang (2018)	Debating	11,693 articles published across 11 journals in the field of technology and innovation management	LDA	Identified the top 10 most popular topics, and for each journal investigated the areas of subspecialty and the effects of editor changes on topic portfolios.
	Randhawa et al. (2016)	Envisioning	321 articles on open innovation (OI) published across 15 management journals (1997-2016)	Leximancer and bibliometric analysis	Identified three distinct areas within OI research and pinpointed specific gaps and underused areas in the organizational, management, and marketing literature.
	Adeva et al. (2014)		1,941 medical journal articles associated with internet-based randomized controlled trial (IBRCT) mapping	Automated text classification (ATC)	Demonstrated the effectiveness of ATC in supporting the screening stage of systematic medical reviews. Achieved overall precision and recall values of up to 84% across a range of machine learning experiments.
	Griffiths and Steyvers (2004)	Envisioning	28,154 abstracts of all *PNAS* papers in the biological, physical, or social sciences (1991-2001)	LDA	Identified hot topics and temporal dynamics of key research trends based on the content of scientific articles.
Envisioning	Antons et al. (2019)	Debating	1,646 strategy articles published in *SMJ* (1984-2014)	LDA and discourse analysis using Linguistic Inquiry and Word Count (LIWC)	Found that the citation premium of newness increases with greater topic focus (which attracts attention) and greater inflow of prior intracollective knowledge (which enhances absorption).

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Table 2. (continued)

Primary Conceptual Goal	Study	Secondary Conceptual Goal	Corpus and Knowledge Domain(s)	Computational Technique(s)	Findings and Implications
Relating	Chen et al. (2019)	Explicating	SSCI database of literature on international research collaborations (IRCs) (1957-2015)	Cocitation network analysis, main path analysis, and bibliographic coupling analysis	Detected three distinct phases of IRC research—"emergence" (1957–1991), "fermentation" (1992–2005) and "take-off" (2006–2015)—and five distinct intellectual areas: drivers of IRC, IRC patterns, effects, networks, and measurement.
	Antons and Breidbach (2018)	Envisioning	641 articles on service innovation and service design published in business and economics journals (1986-2016)	LDA	Constructed a network of 69 topics to illustrate how the topic landscapes of the contextually related, but distinct research fields of service innovation and service design overlap. Generated a research agenda consisting of four research directions and 12 operationalizable guidelines to facilitate cross-fertilization between the two fields.
	Wilden et al. (2018)	Envisioning	3,949 articles citing March's (1991) original article on exploration and exploitation in organizational learning published in any journal listed in the ISI Web of Science database (1991-2016)	Leximancer and bibliometric coupling	Identified potential directions for future research that build upon the themes in March's (1991) original article. Also identified opportunities to reconnect current research to its earlier roots in the behavioral theory of the firm and to link to resource-based theories.
	Asgari & Bastani (2017)		Original strategic management texts on the topic of absorptive capacity.	Hierarchical Dirichlet process (HDP)	Traced the evolution of the concept of absorptive capacity in the management literature for the purpose of knowledge and hypothesis generation.

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Table 2. (continued)

Primary Conceptual Goal	Study	Secondary Conceptual Goal	Corpus and Knowledge Domain(s)	Computational Technique(s)	Findings and Implications
	Wilden et al. (2017)	Envisioning	347 articles on service-dominant logic (SDL) published across all journals within the business and management categories of Scopus and with an impact factor in SSCI (2004-2015)	Leximancer and cocitation analysis	Identified the interdisciplinary theoretical lineage of key themes and core concepts underpinning SDL. Also identified current limitations and future areas for new research to integrate and advance a service ecosystems perspective.
Debating	Tuan et al. (2019)		534 empirical papers on corporate social responsibility communication (CSRC) (2000-2016).	Discourse analysis using LIWC	Measured shifts in the relative popularity of the three primary CSRC theoretical approaches (instrumental, normative and constitutive) and paradigms over time.
	Hopp et al. (2018)	Explicating	1,078 journal articles published on disruptive innovation (1975-2016)	LDA	Uncovered the existence of two increasingly disconnected subnetworks centered around disruptive innovation at the macro level and radical innovation at the micro level.
	Tanskanen et al. (2017)	Envisioning	601 articles on external resource management (ERM) published in 6 academic journals representing 3 management disciplines (1997-2012)	In-depth qualitative content analysis, cross-citation analysis, and computational content analysis.	Detected 6 distinct, yet interrelated themes of ERM research and developed an overall organizing framework and a set of design propositions within each research theme. Identified future research opportunities in ERM.

Sciences (*PNAS*) to describe the corpus of *PNAS* publications. In management, Lee and Kang (2018) map the topics of technology and innovation management by reviewing 11,693 articles published across 11 journals, showing which journals emphasize which topic, and providing readers with guidance about where, ideally, to submit new manuscripts.

Second, the conceptual goal of *envisioning* aims at conceiving a new reality. MacInnis (2011) describes two activities to achieve this goal, namely identifying and revising. Identifying refers to establishing a new "construct, theory, procedure, domain, discipline, or aspect of science that has yet to be apprehended" (MacInnis, 2011, p. 143). Revising, in turn, involves offering new perspectives that question extant knowledge. In the context of a CLR, the goal of envisioning may involve making others aware of what a field has been missing and provide clear definitions of the knowledge domain under investigation. For example, in their *PNAS* review, Griffiths and Steyvers (2004) investigate time trends to identify "hot" and "cold" topics. They provide evidence that Nobel Prize–winning research is typically published during the peak of a respective topic, such as when the majority of articles associated with a topic appear in print. As such, they challenge common wisdom that Nobel laureates initiate and establish new research streams and scientific endeavors. Conversely, Antons et al. (2019) find that studies in management research establishing new thematic streams receive more citations compared to later studies. This offers an alternative perspective on scientific impact that moves the newness of thematic content, rather than attributes of the authors, their academic institution, or the journal into the foreground. Finally, Furukawa et al. (2015) use the CLR method to analyze conference sessions and papers related to the Internet and propose a new process perspective that envisions the evolution of emerging technologies.

Third, a CLR that aims to understand how parts are related to form the whole pursues the conceptual goal of *relating*. This can be achieved by means of differentiating, which entails decomposing the whole into its constituent parts, or by means of integrating different parts into a new entity, which involves identifying similarities between previously disconnected parts (MacInnis, 2011). Several CLRs have pursued the goal of *relating*. For instance, Antons and Breidbach (2018) unearth latent thematic relationships using a topic network to illustrate how the contextually related, but distinct research fields of service innovation and service design overlap, before suggesting ways to integrate and cross-fertilize both fields. Ittipanuvat et al. (2014) use measures of semantic similarity to identify commonalities in research on robotics and gerontology to identify ways how these fields may jointly contribute to the well-being of the elderly. Finally, Höllerer et al. (2020) present a CLR that demonstrates how concepts in management research are interlinked by different theorizing approaches, resulting in a novel architecture of management knowledge.

Finally, the conceptual goal of *debating* intends to challenge commonly held beliefs about an object of inquiry. Debates may be conducted by either advocating or refuting a particular position (MacInnis, 2011). Here, the common assumption is that debating requires scholarly controversy and that audiences need to be persuaded. Thus, CLRs that advocate need to provide evidence in favor of a particular stance, to enhance confidence in their idea, very much like a position paper. In contrast, CLRs that refute need to undermine such confidence, just like a provocative research commentary might do. Indeed, there are multiple published CLRs engaged in debating, with Tanskanen et al. (2017) applying the CIMO (context, intervention, mechanism, outcome) framework to review and develop six priorities that enable more effective evidence-based management. Conversely, Hopp et al. (2018) initiate a debate about disruptive innovation, finding that micro- and macro-level themes in prior research "constitute two sides of the same coin," before developing a research agenda to leverage both.

Practical Guidelines: How to Identify CLR Goals. From the perspective of a first-time user of the CLR method, defining which conceptual goal to pursue may be daunting. First-time CLR users need to differentiate between "what can be produced?" and "what should be produced?" (Gasson, 2003).

This decision involves balancing what is technically feasible, with what is directly useful in terms of new knowledge produced. We recommend that the decision pertaining to the conceptual goal(s) motivating the review should be based on the experience level, and resource constraints of the researcher(s) involved. For the novice user, a sensible starting point would be to commence their CLR with a descriptive goal (i.e., explicating), before focusing on more advanced endeavors (i.e., debating). Importantly, we explicitly acknowledge that researchers, when starting a review project, might have alternative or even conflicting conceptual goals in mind. For instance, they might oscillate between wanting to integrate distinct research streams in a field (the conceptual goal of relating), and seeing the need to refute an influential position advocated in one of the streams (the conceptual goal of debating). To resolve this tension, CLR users will need to engage in iterative cycles of goal specification, exploratory analyses, and possible goal respecification. Even if a dominant conceptual goal has been identified from the outset, addressing it might prove futile once CLR results are available and unexpectedly lead to a dead-end. This makes the process of selecting conceptual goals for CLRs less orderly and unidirectional one might assume at first. Ultimately, CLR users need to embrace this “messiness” and be prepared to revisit their conceptual goals along the CLR process.

Step 2: Operationalize the CLR

Once a tentative conceptual goal has been identified, the researcher needs to *scope the knowledge domain to be reviewed* and *compile the text corpus* for subsequent analysis.

First, diligent scoping of the knowledge domain to be covered is needed despite the vast computational power available, which may make it tempting to favor breadth over specificity of coverage. Importantly, unnecessary breadth of literature coverage introduces noise into the CLR process, which risks diluting results. CLR users therefore need to develop a sufficiently specific scoping heuristic, typically by defining a string of keywords, a particular research field, a certain time period, and/or a journal repository. Doing so requires iterating back and forth between initial specification of a search string, and search results obtained, while tailoring the search approach to the conceptual goals pursued. CLRs aiming at relating, for instance, benefit from a broader scope that provides a bird’s-eye view and greater potential to discover integration or differentiation opportunities. In contrast, CLRs aiming to explicate by summarizing a well-defined research stream benefit from a narrower scope, focused on the core of a literature stream. Ultimately, ensuring the best fit between the knowledge domain to be reviewed, and conceptual goal to be achieved, remains a critical human task with little machine support available.

Second, the human researcher needs to compile the text corpus for subsequent computational analysis. Issues of data access, representativeness, and volume then move into the foreground (Schmiedel et al., 2019). We suggest researchers follow best practices from systematic literature reviews and meta-studies (e.g., Nerur et al., 2008), and use Thomson Reuters’ Web of Science to identify and compile the list of articles to form the text corpus—provided published articles from academic journals are to form the basis of their CLR. This is because the Web of Science is the “most comprehensive database for scholarly work” (Dahlander & Gann, 2010, p. 700), and its Social Sciences Citation Index provides access to peer-reviewed journals, thereby ensuring scholarly quality (e.g., Eom, 2009). Unlike other databases, search results in Web of Science are not constrained by institutional (e.g., university) journal subscriptions. This implies that other researchers can replicate findings by generating the same dataset, if identical keywords are used (Antons & Breidbach, 2018). An alternative to the Web of Science is Scopus.[1] Importantly, however, we recommend a manual screening of the list of articles for problematic inclusions and omissions. Otherwise, the list might include texts that cannot be further processed or are simply unsuitable for the review (e.g., commentaries, retracted articles, articles from predatory journals, etc.). Ultimately, it is beneficial to extract all available meta-data, including titles, author names, journal titles, and the number of citations before downloading respective full-text files to form the text corpus.

Practical Guidelines: How to Operationalize a CLR. From the perspective of a first-time CLR user with limited prior exposure to computational content analytical techniques, operationalizing a first CLR might be challenging. We therefore suggest that first-time users initially build confidence in the CLR method and themselves as CLR users and understand the power and limitations of this method. This is best accomplished by completing a CLR in a familiar knowledge domain. For example, early-career researchers could review the field of their doctoral studies, editors could review the archive of their journal, while practitioners could analyze document-repositories from their professional domain or organization. Conducting such a first CLR will help researchers make more informed scoping and text compilation decisions. In addition, when interpreting CLR outputs against the backdrop of their own knowledge domain, first-time users will likely learn new facets they may not have understood previously. They may be surprised to find out that computational outputs align with their own expertise, but may also learn that some outputs do not immediately make sense to human domain experts. However, none of these insights would be possible if first-time CLR users were to apply computational methods to an unfamiliar text corpus.

Step 3: Choose a Computational Technique

In a third step, CLR users need to *identify and select the computational technique* that is most suitable for the review goal pursued, and the text corpus compiled. In addition, the computational technique needs to be accessible—especially in light of technical capabilities and resource constraints. Each of the four conceptual goals a CLR might pursue can be achieved with a number of computational techniques, but the repertoire of available algorithms will likely evolve in the future. We therefore introduce broader categories of computational techniques and illustrative examples, rather than focusing on specific algorithms with limited half-life. Specifically, computational techniques suitable for text mining in general, and CLRs, in particular, fall into the three broad categories of unsupervised, supervised, and dictionary-based techniques (Antons et al., 2020).

Supervised techniques augment humans' ability to classify large bodies of text into known categories. For instance, the Product Development and Management Association (PDMA) has developed the Body of Knowledge categories to distinguish six subject areas in innovation management research (Griffin & Somermeyer, 2007). By manually assigning a comparatively small number of documents to a subset of existing categories, researchers can train algorithms to detect and classify other texts within these categories. *Unsupervised techniques* do not need an established classification scheme or precategorized documents. Instead, they detect latent patterns in the collection of text documents to be reviewed. The human researcher's task, then, is to interpret and make sense of the patterns revealed by the machine. Finally, *dictionary-based techniques* perform word- and phrase-level analyses to unearth linguistic patterns in texts. For instance, researchers may wish to explore how the rhetorical styles in journal articles evolve with the maturation of a research stream. By using word lists to reflect different rhetorical styles, dictionary-based approaches accomplish this automatically.

We now identify the analytical requirements for each of the four conceptual goals, describe the broader algorithmic class(es) best aligned with these requirements, and highlight exemplary applications to provide future CLR users with reference and inspiration. Table 3 provides an overview of possible matches between algorithmic classes and each of the conceptual goals.

First, the conceptual goal of explicating involves unpacking (i.e., delineating) or consolidating (i.e., summarizing) what is known about an object of inquiry. Achieving these outcomes requires algorithms capable of organizing and mapping component categories of the object of inquiry.

Table 3. Comparison of CLR Algorithms.

Conceptual Goal to Be Pursued	Computational Technique	Suitability for Further Conceptual Goal(s)	Type of Technique	Key Decision Parameters	Trade-Offs to Consider
Explicating	Automated text classification (ATC)		Supervised technique	Setting predefined categories such as research themes or genres.	Finding the right initial dataset. Obtaining a high-quality initial training dataset affects speed vs. accuracy of classification model and resulting output.
Envisioning	Topic modeling using soft clustering, e.g., LDA, LSI, PLSI, NMF	Explicating, relating, debating	Unsupervised technique	Determining the threshold values for meaningful topic loadings.	Making sure the bags of words are meaningfully related. Interpreting the connotative versus the denotative meanings of words in the latent structure of corpora.
	Computer-assisted clustering (CAC)		Unsupervised technique	Selecting the groupings of objects to visualize for generating insightful categorizations.	Managing the frequency of interaction, number of iterations, and computational resources required to pinpoint distinctive clusters of ideas.
Relating	Semantic extraction	Explicating	Dictionary-based approach and also supervised techniques	Choosing how to quantify and display the conceptual structure of text corpora.	Balancing the fine-grained degree of control available through linguistic analysis versus the programming needed to customize the output.
	Topic modeling using hard clustering, e.g., hierarchical Dirichlet processes (HDP)		Unsupervised technique	Selecting the number of nested hierarchical levels and relevant timeframe for bounding the corpora.	Balancing the number of clusters with the complexity of accurately representing the underlying latent ideas.
Debating	Rhetorical discourse analysis	Relating	Dictionary-based approaches and also supervised techniques	Configuring the appropriate levels of analysis: word, sentence, document (inter- and intra-textually).	Evaluating, in context, the interplay between the substantive and the stylistic elements of the discourse under study.

Supervised techniques in general (Lloret & Palomar, 2012) and text classifiers in particular are of interest because they enable CLR users to identify meaningful dimensions of the object of inquiry ex ante, obtain algorithmic support for understanding the factors that discriminate scientific texts assigned to one category as opposed to another (completed when training the classifier), and automatically categorize scientific texts at scale (completed in running the classifier). A broad range of automated text classification (ATC) algorithms exist, including techniques such as naïve Bayes, k-nearest neighbors, or support vector machines (Adeva et al., 2014). For example, Adeva et al. (2014) applied ATC to screen 1,941 medical research articles associated with 61,752 unique terms based on the article's title, author list, journal, keywords, and abstract.

Second, the conceptual goal of envisioning involves establishing a new object of inquiry that merits dedicated research attention (i.e., identifying), or rethinking and redirecting an already established line of inquiry (i.e., revising). Given the aspiration to discover newness by reviewing what has already been published, CLR users pursuing the goal of envisioning can benefit from algorithms that augment their ability to detect latent, that is, previously invisible and perhaps unknown, thematic patterns in large text corpora. Unsupervised techniques designed to assemble texts into coherent thematic clusters, typically referred to as topics, are particularly suitable. Algorithms employed for inducing hidden topic structures from texts, also known as topic modeling, expanded notably over the past decade. This includes techniques such as latent semantic indexing / latent semantic analysis (Deerwester et al., 1990), probabilistic latent semantic analysis (Hofmann, 2001), non-negative matrix factorization (Xu et al., 2003), and latent Dirichlet allocation (LDA; Blei et al., 2003). LDA, the most established topic modeling algorithm available today (Blei, 2012),[2] assumes that any text document can be represented by a collection of topics, with each text document being characterized by a particular distribution of topics.

As a soft clustering technique, LDA allows each document to be related to more than one topic, rather than forcing each document on exactly one topic (hard clustering) and has been used, for example, in Griffiths and Steyvers's (2004) analysis of abstracts published in the *PNAS*. Beyond topic modeling with LDA, computer-assisted clustering (CAC) approaches may prove valuable in envisioning (e.g., Grimmer & King, 2011). CAC incorporates a broad set of clustering algorithms designed to group a given set of input objects (e.g., scientific texts) into distinct categories (so-called clusters or partitions, such as scientific topics). Most importantly, CAC differs from individual clustering algorithms (i.e., LDA) by enabling human researchers to compare the outputs of numerous algorithms, thereby identifying the most insightful categorization of the thematic content. Hence, CAC appears well suited to support envisioning by exposing human researchers to diverse and potentially novel ways of grouping scientific texts in a domain (Grimmer & King, 2011).

Third, CLR users pursuing the conceptual goal of relating seek to decompose a field of inquiry into its constitutive parts (i.e., differentiating), or to link previously disconnected parts of a line of inquiry (i.e., integrating). This requires identifying conceptual building blocks of a knowledge domain, but also understanding the linkages between them. CLR algorithms are hence needed to both extract content categories from text, and to map their relationships. Unsupervised text clustering algorithms meet these requirements—especially when supplemented by appropriate visualization techniques. For example, semantic extraction tools like Leximancer are a useful means to compute, visualize, and navigate networks of concepts (Doan et al., 2006). Semantic extraction seeks to capture the likely intended meaning of the actual words used to compose the topics within a given document. It does so by analyzing the language composition and syntax of words within the article's sentences. To date, CLRs using semantic extraction techniques have been conducted in open innovation (Randhawa et al., 2016), organizational learning (Wilden et al., 2018), and service-dominant logic (Wilden et al., 2017) studies.

We consider it noteworthy to point out that a significant advantage of LDA and other topic modeling algorithms vis-à-vis semantic extraction tools is that their outputs can be further processed, for example, by constructing network graphs.[3] Here, topics are depicted as the nodes, with the size of the node indicating the number of text documents loading on the respective topic. Topic co-occurrence is depicted as ties, with the strength of the tie between two topics indicating the number of text documents loading on both topics. Such a network graph depicts the salience of—and interplay between—distinct topics in a corpus, thus supporting CLR users pursuing the goal of relating. Importantly, topic graphs enable CLR users to quantify the strength of relationships between topics or group of topics, which serves as a proxy for conceptual similarities or differences, while also identifying topics linking disconnected topics—a meaningful starting point for integrating efforts. For example, Hopp et al. (2018) computed a topic network of two distinct, but conceptually related subfields in the disruptive innovation literature, and proposed ways to encourage cross-fertilization between these subfields.[4]

Finally, CLR users pursuing the goal of debating seek to fuel scholarly controversy in a line of inquiry either by corroborating a particular position (i.e., advocating) or by undermining it (i.e., refuting). CLR users therefore require techniques that enable them to quantify the extent to which a single scientific text, or indeed a collection of texts by the same author or on a similar topic, supports or criticizes established knowledge. Discourse analysis methods such as linguistic analysis and rhetorical analysis can unpack the nature of an ongoing debate in the literature. Linguistic analysis focuses on quantifying patterns of word choice, while rhetorical analysis focuses on quantifying patterns of connections among words used (McNamara et al., 2014). Such patterns reflect the extent to which the content of a text is narrative versus informational, simple versus complex, concrete versus abstract, and cohesive in its references and causality (Graesser et al., 2014).

There are a number of useful software tools presently available. For linguistic analysis, the Linguistic Inquiry and Word Count (LIWC) software (Pennebaker et al., 2015) has been used in CLRs exploring corporate social responsibility (Tuan et al., 2019) and the scientific impact of topic newness (Antons et al., 2019). For rhetorical analysis, the Coh-Metrix software (McNamara & Graesser, 2012) has been used to analyze the persuasiveness of—and stylistic shifts in—the presentation of scientific arguments (Bruss et al., 2004; McCarthy et al., 2006), to examine cross-cultural variation in scientific discourse (McCarthy et al., 2007), or to detect obfuscation, deception, or possible fraud in scientific texts (Markowitz & Hancock, 2016).

Practical Guidelines: How to Select Computational Techniques. Researchers interested in conducting a first CLR may hold the common misconception that, to benefit from the analytical techniques underpinning CLRs, one must learn and master programming languages like R or Python. This is not the case. In fact, tools for semantic extraction such as Leximancer provide human researchers with a graphical user interface to display networks of concepts and themes in text corpora for visual interpretation—without the need to master programming languages (Cretchley et al., 2010). Unless researchers are already familiar with programming languages, or are comfortable learning R or Python, using tools for semantic extraction might be a more effective approach for the first-time user of CLRs.[5] However, an essential trade-off to consider when using a tool like Leximancer vis-à-vis customized machine learning approaches is the degree of control versus the customizability of the output. For example, Leximancer offers only limited control over the parameters used to quantify and demarcate the conceptual structure of text corpora (Leximancer, 2018). Although this simplifies the number of decisions that researchers need to make, it also constrains the amount and types of outputs available to interpret. If, however, future researchers intend to be in full control of the analytical process, and seek to describe this in detail in order to further increase the transparency and replicability of a CLR, having a solid command of programming languages like R or Python will be a definite asset.

Step 4: Perform the Content Analysis

The fourth step of the CLR method is contingent on the computational techniques chosen in step 3 of our roadmap. As such, not all activities we describe will necessarily be part of *every* CLR. In the most general sense, however, the content analysis of the CLR method can be structured into (a) preparing the data, (b) calibrating the algorithm, and (c) enriching the algorithmic output.

First, the text corpus assembled during Step 2 needs to be *preprocessed* for further algorithmic analysis. Unlike bibliometric literature reviews or meta analyses, CLRs focus on the thematic content, as contained in the abstracts or the full texts of a scientific article. Text preprocessing is not yet fully appreciated in the methods literature, yet it is a critical determinant of both the input quality and the validity of a CLR (Rüdiger et al., 2017). For any CLR, all text files need to be converted into a machine-readable format. This might require optical character recognition (OCR) software whenever texts are stored as images (e.g., JPEG files), with multiple proprietary packages available today. When semantic extraction tools like Leximancer are used for the content analysis, text preprocessing is typically limited to the conversion of images into text. However, whenever more complex and powerful algorithms like LDA are to be used, additional activities become necessary to reduce the variability of human language.

The seven main activities to consider are the following: (a) All text needs to be converted to lowercase (or uppercase); (b) all punctuation needs to be excluded; (c) meaningless "stopwords" (e.g., "she," "the," "thus") as well as (d) infrequent terms that were used in less than 0.1% of all articles should also be excluded (e.g., Blei et al., 2003, Rüdiger et al., 2017). Another source of word variability is the grammatical tense with which individual words can be used. Therefore, (e) words should be reduced to their word "stem" (e.g., the words "service," "services," and "served" can be reduced to their stem "serv*"), while a technique called lemmatization can be used to group inflected forms of a word together into a single representation, the lemma. Another aspect that warrants attention in the English language, are compound words such as "literature review," which carry a joint meaning that has to be identified, in order for the algorithmic analysis to avoid taking the individual words "literature" and "review" into consideration. So-called n-grams can be used here (f) that apply statistical or rule-based techniques to identify compound words (e.g., Wang et al., 2007). Finally, (g) we suggest removing reference lists, as they typically do not add to the content of scientific articles but increase language variability and therefore statistical noise during the analysis.

Second, when using proprietary software such as Leximancer, researchers may not be able to *calibrate underlying algorithms*. If, however, the analysis is conducted via programming languages, researchers should calibrate the algorithm used to improve performance. For example, if unsupervised clustering techniques like LDA, LSA, or CAC are used, the number of topical clusters to be extracted needs to be specified. This is challenging, especially when pursuing the goal of envisioning or relating, whereby emerging topics or hidden relations are to be identified. However, there are procedures available that help researchers identify the optimal number of topics to be extracted by a given algorithm, and thereby achieve the best possible fit with the underlying textual data (e.g., Hopp et al., 2018). For hierarchical clustering techniques like HDP, visual techniques such as dendrograms or so-called stopping rules that help determine the optimal number of hierarchies are useful (e.g., Caliński & Harabasz, 1974).

Third, regardless of the choice of algorithm and conceptual goal pursued, CLR users need to *validate and supplement the algorithmic outputs* to generate new insights. This includes checking algorithmic outputs for accuracy, plausibility, and compatibility with their understanding of the knowledge domain. This is especially important when using unsupervised techniques, which require the human researcher to label the algorithm-extracted outputs. For instance, a CLR using LDA yields a list of topics with associated terms, as well as indicators highlighting how strongly each article within the text corpus is related to each topic (e.g., Blei, 2012). We suggest researchers extract and review the top terms associated with each topic within their text corpus, along with the titles, abstracts, and keywords of all articles loading highly on each respective topic. Making sense of this information is an intensive and time-consuming step, comparable to the analysis of qualitative data, and ideally performed by domain experts. In our own experience, we found it beneficial when all members of a research team used this information to independently assign descriptive labels to each topic highlighted by the algorithm. Once completed, established approaches from qualitative research like intercoder reliability (Miles & Huberman, 1994) can be used to compare and assess initial results. The reliability of the generated labels can be further tested and verified by external panels of domain experts.

Researchers might also solicit additional outputs, visualize their results, and perform a set of sensitivity and statistical analyses to enhance the quality of insights generated by the CLR method. For example, regression analysis can be used to estimate topics' trajectories (e.g., Griffiths & Steyvers, 2004), network analyses can illustrate relationships between topics (e.g., Antons & Breidbach, 2018), heatmaps can help discover research hotspots and gaps, and topic impact profiles can help uncover patterns of knowledge consumption (e.g., Rüdiger et al., 2017).

Practical Guidelines: How to Perform the Content Analysis. From the perspective of a first-time user, one intuitive way to start a CLR may be to utilize ready-to-use software. However, given the conceptual goals of the review at hand, we suggest that this will (in most cases) not be possible. The most effective way to advance CLR projects quickly is through interdisciplinary research teams. Domain experts should identify technical experts as potential research collaborators, or those comfortable in learning CLR methods. As a case in point, prior training in computer science and advanced statistics will make it considerably easier to learn and understand algorithms like LDA or other text mining techniques. Conversely, researchers with deep technical expertise interested in applying CLRs will benefit from teaming up with domain experts, who can guide the CLR process by interpreting computational outputs and delineating sufficient contributions from the findings.

When performing the content analysis of a CLR, human researchers are fully exposed to, and required to interact with, computational algorithms. A critical perspective and reflective use of computational algorithms is therefore all the more vital during this process step. We noted earlier that computational approaches are meant to amplify and augment, not replace the "gold standard" of human reading and interpretation (Grimmer & Stewart, 2013). However, the sheer amount of textual data and information to process is likely too demanding. Moreover, human researchers can be prone to errors caused by overapplying prior experience, past mental models, or knowledge structures. This is why, when used in conjunction with human insights, algorithms can enhance the rigor of CLRs compared to MLR approaches. To ensure the reliability and validity of CLRs, we suggest that, when performing CLRs, human researchers evaluate whether or not the output and predictions of their models have properly deconstructed the relevant characteristics of the corpus under examination (e.g., Chang et al., 2009). Consider the example of a research team investigating an entire field of research covering many different subareas. Here, each member of the team should inspect the subarea they are most familiar with to see whether the results of the CLR exhibit face validity.

Step 5: Generate Original Insights

In a fifth step, CLR users need to apply their domain knowledge to transform the algorithmic outputs into meaningful insights. Importantly, these insights should be aligned with, and support, the conceptual review goal pursued, thereby creating value for the target audience—be it newcomers or experts in science, management, or policy. We know from experience that this is by far the most challenging and time-consuming step of any CLR project, and provide some guidance resulting from our own work in this area.

The CLR algorithms available to date help structure the knowledge domain and produce new stimuli for *human discovery*. This process of discovery, however, only unfolds when comparing and contrasting algorithmic outputs with existing assumptions, established theory, or one's own expectations and hypotheses. Oftentimes, original insights will only emerge by iterating back and forth between calibrating the algorithm, enriching the algorithmic outputs, and interpreting them in light of the conceptual goal pursued. At times, this will also involve exploring alternative CLR algorithms or even integrating other review methods. The concrete options available to the CLR user will vary substantially as a function of the conceptual goal pursued, and the class of algorithms employed for this purpose. Just like when conducting qualitative case studies intending to inductively build theory, one should iterate back and forth between data and literature. Indeed, researchers who embrace the iterative nature of the CLR method will likely increase the probability of meaningful discovery as part of their work. They will hence be better positioned to articulate their overall contribution to the debate in the field and publish their CLR in a quality outlet. Ultimately, and despite major advances in text mining and other areas of machine learning, today's computational content analysis techniques still have a long way to go before they can match the human ability to understand meaning (Grimmer & Stewart, 2013). CLR algorithms should therefore be perceived as increasingly valuable, but necessarily imperfect tools that *facilitate and stimulate, rather than substitute* for human insight.

Practical Guidelines: How to Generate Original Insights. We suggest that first-time users of the CLR method explore the capabilities of this novel review method by attempting to generate insights for a wide variety of potential beneficiaries—be it newcomers or experts in science, management, or policy. For example, if researchers who are about to enter a new field, or who want to get a better understanding of their current field, are the intended target audience, insights generated in a first CLR could aim to answer one of the following questions: Which authors, author networks, institutions, and funding sources spark and catalyze the introduction of new topics and drive the evolution of existing topics? To what extent do topic, author, institutional, and funding networks overlap? Who are the topic leaders? What are their institutional affiliations and funding sources? By revealing previously unnoticed gaps and trends in scholarship that may otherwise be missed, CLRs could also be utilized by editors and reviewers to guide the future development of their journals, examine the effects of changes in editorial policies, or generate ideas for new special issues. Conference organizers might also benefit from the CLR method and use it to identify tracks and assign papers accordingly. Finally, junior scholars (e.g., PhD students) or those new to a discipline or field of study could use CLRs to rapidly and efficiently obtain an unbiased overview of a domain.

Step 6: Present the Findings

The sixth and final step of the CLR method involves presenting the findings and communicating them in a digestible form for scholarly consumption. Future researchers could present and communicate their CLR findings using one of the following four forms of synthesis: (a) research agenda, (b) taxonomy, (c) alternative models, and (d) meta-theory (Post et al., 2020; Torraco, 2016).

A *research agenda* identifies and elaborates new questions that help scientific fields progress. Developing a research agenda is especially relevant for those intending to pursue the explicating goal. Valuable CLRs go beyond synthesizing the state of the art. Synthesis can be seen as a means, but not as the end of explicating. Helpful explicating CLRs will use their analyses to identify gaps in knowledge *and* guide future work, for example, in the form of actionable research priorities comprising a holistic agenda. Research agendas can be used in conjunction with a *taxonomy* that categorizes the new knowledge obtained through a CLR along relevant dimensions.

Alternative models can synthesize and represent findings of a CLR to illustrate or reveal gaps. For example, following the conceptual goals of explicating, relating, and debating, algorithms like LDA enable researchers to use a broad array of visualization techniques that dramatically increase the value of the insights generated. For example, when pursuing the conceptual goals of explicating, creating topic networks, and delineating their evolution over time helps to illustrate the thematic evolution of a knowledge domain, thus reconceptualizing established knowledge. Similarly, when the goal of envisioning aims to identify unknown and latent trends in a field, heatmaps of salient topics can visually depict the ebb and flow of "hot" or promising, and "cold" or stagnating topics. Heatmaps can thereby provide the basis for new taxonomies to guide future research (Antons et al., 2016).

Meta-theory bridges knowledge across disparate domains or disciplines. Such a contribution emerges mainly from the conceptual goals of envisioning and debating. By scoping a CLR based on unsupervised techniques to span a wide range of knowledge domains, researchers may uncover latent or hidden patterns in the representation of ideas within and across different knowledge domains. By identifying areas of constructive overlap among domains or disciplines, researchers may reveal shared concepts, and common foundations thus resulting in meta-theory (e.g., Brust et al., 2017).

Practical Guidelines: How to Present the Findings. Whether researchers are first-time or experienced users of CLRs, we recommend explicitly stating which of the four forms of synthesis represents their result and contribution. For instance, if the CLR yields new information about unanswered research questions and heretofore untested research propositions, then this may constitute the underpinnings for a new research agenda and should be presented as such. Or, if researchers generate insights about certain dimensions that provide a new and useful representation of previously undefined categories of knowledge within their CLR, then this may serve as the basis for a new taxonomy and should be labeled as such. For expert users of CLRs, we recommend focusing on actively leveraging CLRs in combination with other computational techniques and key elements of manual reviews to engage more deeply in theory-building. This could involve focusing on alternative models, meta-analyses, and meta-theory, because CLRs may accelerate theory development by enabling advanced users to allocate their time and effort on developing new insights and synthesizing findings—higher-level tasks in which people naturally outperform machines.

Discussion

In this article, we introduce and define the CLR method as a structured process of conducting systematic literature reviews. This process augments human researchers' information processing capabilities by drawing on increasingly powerful machine learning algorithms when analyzing the thematic content of a scientific text corpus in a specific knowledge domain (e.g., a research topic, academic journal, or scientific field) in a way that is scalable and potentially real-time capable. As such, the CLR method offers exciting new possibilities to those seeking to synthesize large bodies of literature in view of shaping the ongoing discourse in science, practice, or policy. To lower barriers to adoption and make the CLR method accessible to novice and experienced researchers accustomed to manual review approaches, we provide comprehensive and actionable methodological guidance on how to design, conduct, and document CLRs. We present novel and important guidance in the form of a six-step roadmap, covering the entire CLR process. Importantly, we identify and explain key design decisions along the CLR process and highlight the importance of human decision-making. With a special emphasis on first-time users of CLRs, Table 4 provides an overview and summary of these practical guidelines. While currently available CLR algorithms will continue to evolve over time, the CLR method and six-step roadmap provided will continue to serve as a useful guide to those seeking to conduct impactful, rigorous, and replicable reviews of increasingly large and complex scientific text corpora.

Table 4. Summary of Practical Guidelines With a Special Emphasis on Novice Users.

Step	Practical Guideline(s) and Question(s) to Consider
Step 1: Begin with a conceptual goal	How to identify CLR goals? • Differentiate between "what can be produced?" and "what should be produced?" (Gasson, 2003). This decision involves balancing what is technically feasible, with what is directly useful in terms of new knowledge produced. • Your decision about the conceptual goal(s) motivating your review should be based on your level of experience, and any resource constraints of you and/or your team. • A sensible starting point would be to commence your CLR with a descriptive goal (i.e., explicating), before focusing on more advanced endeavors (i.e., debating).
Step 2: Operationalize the CLR	How to operationalize a CLR? • Initially build confidence in the CLR method and yourself as a CLR user and understand the power and limitations of this method. This is best accomplished by completing a CLR in a familiar knowledge domain. • If you are an early-career researcher, you could review the field of your doctoral studies. Or, as an editor, you could review the archive of your journal. Or, as a practitioner, you could analyze document-repositories from your professional domain or organization. • Conducting a first CLR will help you make more informed scoping and text compilation decisions later in the process. • You will likely learn new facets about your knowledge domain after interpreting CLR outputs. • You may be surprised to find out that computational outputs align with your own expertise, but may also learn that some outputs do not immediately "make sense." This is to be expected. • Always remember that none of your insights would be possible if you were to apply computational methods to an unfamiliar text corpus.
Step 3: Choose a computational technique	How to choose a computational technique? • You may have the common misconception that, to benefit from the analytical techniques underpinning CLRs, one must learn and master programming languages like R or Python. This is not the case. In fact, tools for semantic extraction such as Leximancer provide a graphical user interface to display networks of concepts and themes in text corpora for visual interpretation—without the need to master programming languages (Cretchley et al., 2010). • Unless you are already familiar with programming languages, or are comfortable learning R or Python, using tools for semantic extraction might be a more effective approach for the first-time user of CLRs. • An essential trade-off to consider when using a tool like Leximancer vis-à-vis customized machine learning approaches is the degree of control versus the customizability of the output. For example, Leximancer offers only limited control over the parameters used to quantify and demarcate the conceptual structure of text corpora (Leximancer, 2018). We consider this trade-off appropriate, especially for first-time users. • Tools for semantic extraction simplify the number of decisions you need to make, but also constrain the amount and types of outputs available to interpret. If, however, you intend to be in full control of the analytical process, and seek to describe this in detail in order to further increase the transparency and replicability of a CLR, having a solid command of programming languages like R or Python will be a definite asset.

(continued)

Table 4. (continued)

Step	Practical Guideline(s) and Question(s) to Consider
Step 4: Perform the content analysis	How to perform the content analysis? • The most effective way to advance CLR projects quickly is through interdisciplinary research teams. • If you are a domain expert, identify technical experts as potential research collaborators, or those comfortable in learning CLR methods. • If you possess deep technical expertise and are interested in applying CLRs, you will benefit from teaming up with domain experts, who can guide the CLR process by interpreting computational outputs and distilling sufficient contributions from the findings.
Step 5: Generate original insights	How to generate original insights? • Explore the capabilities of CLRs by generating insights for a wide variety of potential beneficiaries—be it newcomers or experts in science, management, or policy. • For example, if researchers about to enter a new field, or who want to get a better understanding of their current field, are your intended target audience, insights generated in a first CLR could aim to answer one of the following questions: o Which author(s), author networks, institutions, and funding sources spark and catalyze the introduction of new topics and drive the evolution of existing topics? o To what extent do topic, author, institutional, and funding networks overlap? o Who are the topic leaders? o What are their institutional affiliations and funding sources? • If you are an editor or reviewer of a journal, you could use CLRs to reveal previously unnoticed gaps and trends in scholarship that may otherwise be missed, thus guiding the future development of your journals • You could also examine the effects of changes in editorial policies, or generate ideas for new special issues. • If you are a conference organizer, you might benefit from the CLR method and use it to identify tracks and assign papers accordingly. • If you are a junior scholar (i.e., Ph.D. students) or new to a discipline or field of study, CLRs can help you to rapidly and efficiently obtain an unbiased overview of a domain.
Step 6: Present the findings	How to present the findings? • Explicitly state which of the four forms of synthesis represents your result and contribution. • For instance, if your CLR yields new information about unanswered research questions and heretofore untested research propositions, then this may constitute the underpinnings for a new research agenda and should be presented as such. • Or, if you generate insights about certain dimensions that provide a new and useful representation of previously undefined categories of knowledge, then this may serve as the basis for a new taxonomy and should be labeled as such. • Leverage CLRs in combination with other computational techniques to engage more deeply in theory building. • CLRs enable advanced users to allocate their time and effort on developing new insights and synthesizing findings through alternative models, meta-analyses, or meta-theory.

Strengths and Limitations of the CLR Method. The CLR method offers a number of benefits when appropriately directed by human researchers. For one, provided the six process steps are documented in a transparent and comprehensive manner, quantitative results are replicable. Specifically, researchers who use the same algorithm to analyze the same corpus will obtain the same quantitative output, even if their eventual theoretical interpretation of this output varies due to different disciplinary backgrounds or theoretical lenses applied. Second, the CLR method we put forth—especially when relying on unsupervised techniques—enhances the objectivity of the CLR process by reducing the need to apply predefined mental models or existing knowledge structures on the corpus of interest. This increases the reliability of reviews by reducing systematic biases or judgment errors arising from either too much or too little familiarity with the literature. The CLR method also reduces idiosyncratic decision-making by offering a standardized framework through which the human researcher structures the frequency and intensity of human-computer interaction. This reinforces the rigor of the computational review process, in comparison to current methods.

All literature review approaches, including the CLR method, necessarily have limitations. One important limitation, particularly for first-time users of CLRs, is the possible overreliance on standardized outputs generated by the "black box" of underlying algorithms. Researchers may place too much trust in the algorithm or tool at hand and may be overconfident when evaluating its results. Those who are technically skilled, but new to a scientific domain, may be especially susceptible to this problem, which could lead to blindly accepting CLR results. Assembling a research team of scholars with technical *and* domain expertise may address this challenge. Another limitation may be a tendency to overscope the review in terms of the range of knowledge domains and types of documents included in the text corpus. Although the CLR method makes large-scale analyses of diverse bodies of unstructured documents feasible, this does not mean that analyzing all of the available documents is always the best approach. Finally, as we explained at the outset, conducting literature reviews involves "a critique of the extent, nature, and quality of evidence in relation to a particular research question" (Siddaway et al., 2019, p. 1). Although a noteworthy strength of CLRs is the ability to reveal previously undetected patterns or connections among texts, this is also a potential source of bias if the underlying quality of these texts is not properly considered. While CLRs can accelerate the analysis of an extremely large *quantity* of documents in a corpora, the CLRs cannot ascertain the actual *quality* of these documents and the nature of the knowledge contained therein.

As Siddaway et al. (2019) highlighted, "The best reviews synthesize studies to draw broad theoretical conclusions about what a literature means, linking theory to evidence and evidence to theory" (p. 1). Today, however, the technical capabilities of the algorithms enabling CLRs do not allow us to make fine-grained evaluations of epistemology, or to critically discern the relative merits of the evidentiary links underpinning key theories. This is precisely why, as we explained in our earlier roadmap and practical guidelines, *people, and not machines* should be central to any proposed implementations of CLRs. This is especially true when researchers are attempting the challenging task of making sense of and synthesizing new and complex information to build theory. We emphasize that MLRs remain the gold standard in conducting systematic literature reviews and continue to enhance our broader understanding of various knowledge domains in ways that even the most advanced algorithms are so far unable to achieve. Indeed, although our study strongly advocates for the use of CLRs by novices and experts, we do so with the recognition that CLRs are not necessarily the most suitable approach for conducting literature reviews in every research setting or for answering every research question. Here is where the judgment, experience, and scholarly standards of the researcher(s) conducting the CLRs must play an essential role now and into the foreseeable future to carefully avoid the mis-specification or mis-application of CLRs. While fully acknowledging the aforementioned known limitations of CLRs, we contend that CLRs are still of considerable value to researchers when used correctly and in line with the guidelines provided in this paper (see Table 4).

Leveraging the CLR Method to Enhance Theory Development. The CLR method enables theoretical contributions by providing a scalable way to investigate, and shape the thinking about research fields, phenomena, topics, or other areas of interest (Post et al., 2020). The approach to CLRs that we advocate for addresses calls for literature reviews to develop theory and be both integrative and generative. The CLR method supports researchers in being integrative by helping to analyze and synthesize existing research at scale and in unprecedented levels of granularity (Torraco, 2016). This augments a human researcher's ability to generate new ideas and, ultimately, produce new theory (Gatrell & Breslin, 2017). The CLR method may therefore foster theory development by exposing emerging perspectives; by contrasting, specifying, and (re)structuring existing theoretical constructs, or by helping scholars understand the underlying assumptions in text corpora (Post et al., 2020).

First, CLRs pursuing the goal of envisioning reveal emerging phenomena and provide clear definitions within the context of a discipline, which is important when attempting to foster theory development. This is because socio-technical changes to managerial practice can result in existing theories and scientific perspectives becoming obsolete (Post et al., 2020). By exposing emerging theories and perspectives that manual reviews may not be able to detect in large and complex scientific text corpora, the CLR method ensures scientific research benefits from these perspectives and is thus sufficiently aligned with current managerial practice. CLRs can also trace the historical development and diffusion of a potentially outdated theory, thus providing important signals to future research when to abandon these outmoded ideas.

Second, contrasting, specifying, and (re)structuring existing theoretical constructs refines existing theory (Fisher & Aguinis, 2017). In this context, Post et al. (2020) explain that construct clarity is critical when building new theory, or when attempting to compare, replicate, or aggregate empirical work (Suddaby, 2010). The CLR method enables researchers to achieve these goals by delineating precise definitions and by differentiating these from related concepts. For example, combining multiple computational techniques to analyze the same corpus may help to synthesize alternative models that clarify constructs or test boundary conditions.

Third, the CLR method aids to the development of theory by analyzing and improving the understanding of the assumptions underlying scientific text corpora (Burrell & Morgan, 1979). Here, CLRs used to pursue the conceptual goal of debating may change commonly held beliefs about an object of inquiry (MacInnis, 2011). New theory therefore not only emerges by identifying what individual assumptions are, but also from understanding their significance, and potentially from evaluating their consequences (Post et al., 2020). For example, CLRs can be scoped to encompass multiple knowledge domains, thus synthesizing meta-theory in terms of how similar assumptions in the literature are represented, and the extent to which these representations converge or diverge across fields. Similarly, CLRs can identify theoretically coherent clusters of authors, as well as their links or lack thereof, thus highlighting prevailing and competing assumptions.

Combining CLRs With Alternative Review Methods. Future researchers could combine the CLR method with other approaches, including bibliometric analyses, meta-analyses, and narrative analyses, thereby leveraging the respective strengths of each to advance the conceptual goals of explicating, envisioning, relating, and debating.

First, for researchers pursuing the conceptual goal of *explicating*, the CLR method and *meta-analyses* complement each other. The CLR method enables researchers to identify and measure content-related sources of variation in effect sizes across studies, thereby amplifying the explanatory power of meta-analyses. For example, identifying how frequently certain keywords co-occur (e.g., KBV, RBV, TCE), or how frequently certain topics are combined (e.g., knowledge, resources, and transaction costs) within a set of studies, may be a meaningful predictor of the effect size. As such, the CLR method may enhance meta-analyses by making it easier to include a wider array of explanatory variables when synthesizing previous findings and appropriately positioning these findings in context. For example, CLRs may be used to analyze open-ended survey responses. This has the potential to incorporate a richer set of data to investigate the phenomenon of interest (Pietsch & Lessman, 2018). The CLR method may also be useful in detecting outliers or exceptions in a set of studies under consideration for a meta-analytic review (Upreti et al., 2016).

Second, researchers pursuing the conceptual goal of *envisioning* could complement machine learning techniques including LDA with *bibliometric* techniques to make others aware of what a field has been missing. LDA and other text clustering algorithms are unable to extract obscure and infrequently discussed topics that appear only once or twice across a text corpus (McKinley et al., 1999). However, these topics might establish a new research stream. We therefore suggest using *bibliometric* techniques such as cocitation analysis in this context. If articles have cocitations, one assumes that this is an indicator of knowledge confluence. Cocitations of articles covering different topics may indicate that topics are being recombined, that a research field is maturing, or that new meta-theory is emerging.

Third, researchers pursuing the conceptual goal of *relating* might also consider combining the CLR method with *bibliometric analyses* such as bibliographic coupling. This enables one to trace the production and consumption of knowledge within and across disciplines (Chen et al., 2019). Analyzing backward citations, for instance, might provide insights into the shared, potentially interdisciplinary intellectual heritage of a field. In contrast, when applied to forward citations, bibliographic coupling can uncover how knowledge from one domain is consumed in others.

Finally, researchers pursuing the conceptual goal of *debating* may find combining the CLR method with *narrative analyses* helpful. Specifically, CLRs complemented by automated frame analysis (AFA) or automated narrative analysis (ANA) hold great potential. While AFA helps to discern the framing of an article's content (Odijk et al., 2013), ANA helps to determine the actors, actions, and their positions within the actual narrative or story framed in the article (Franzosi, 2010). Given the importance of framing and narratives in translating evidence into management practice, these techniques will be valuable for researchers in making knowledge more accessible to practitioners.

Conclusion

The large volume, rapid growth, and increasing complexity of scientific knowledge makes it equally important and challenging to manually conduct rigorous and impactful literature reviews. The CLR method helps to overcome this challenge by augmenting human researchers' insights and judgment with computers' speed and efficiency—hence making literature reviews scalable and real-time capable. The CLR method not only increases the effectiveness and efficiency of systematic literature reviews, but also opens avenues for new questions to be asked, and conceptual goals to be pursued. Moving forward, the continued growth in the variety of data sources and digital archives available to researchers strongly suggests that ample opportunities to apply the CLR method to text corpora beyond academic literature will arise in the foreseeable future. Examples for text corpora to be reviewed other than research articles include patent applications, newspaper articles, corporate archives, customer and user-generated content (e.g., blog posts, community and social media entries), or government repositories, reports, and records. Ultimately, we believe that the CLR method, as part of the wide array of technological advances in the broader field of computational social sciences, offers a promising new direction for management research and beyond. We encourage future researchers to continue to place human decision-making at the forefront of this endeavor, and use the CLR method to accelerate scholarly inquiries and help the research community proactively adapt to and benefit from the explosive growth of knowledge. To answer T. S. Eliot's question that we posed earlier—"Where is the knowledge we have lost in information?"—we recommend that scholars begin actively applying CLRs in their research.

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Notes

1. Most scholars are familiar with Google Scholar. While this service enables a quick and comprehensive search for literature, it currently does not provide a way to extract meta-data, thus limiting practicality for CLRs.
2. Blei (2012) highlights that the term *latent Dirichlet allocation* reflects on the characteristics of the algorithm. First, the model is *latent* as it infers a hidden structure. Second, it assumes that topics have a *Dirichlet* distribution across documents. And third, words are *allocated* to topics by applying this distribution.
3. There are also algorithms to compute so-called correlated topic models that reveal and help to visualize interdependencies among topics. Blei and Lafferty (2007), for instance, compute a correlated topic model to map the topic landscape of *Science* between 1990 and 1999 with special emphasis on the relationships between topics.
4. Hard clustering algorithms such as hierarchical Dirichlet processes (HDP) are an alternative to soft clustering and can prove valuable for CLR users pursuing the conceptual goal of relating. HDP was originally developed to identify how topics relate to each other in a hierarchical order (Teh et al., 2006) and can help CLR users unearth topic hierarchies—which might inform differentiating or integrating activities. HDP is also well suited for estimating how clusters of knowledge within text documents evolve across multiple text corpora over time (Zhang et al., 2010).
5. For additional information on content analysis resources on the internet, please see www.terry.uga.edu/_contentanalysis.

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