Possible uses of automation technology for optimizing funder's workflow

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Executive Summary

Research environments are expected to drastically change with the recent advancements in artificial intelligence and automation tools. *The Open Science Committee* of *The Netherlands Organisation for Health Research and Development* has commissioned this project to identify tools that could enhance funders' workflow and support them in ensuring value in research, while stimulating open science and research innovation. In a scoping review and stakeholder consultations, 34 already existing tools and services were identified and grouped according to the task they aim to facilitate (automation of knowledge synthesis, writing of proposals or publications, conducting pre-review checks, finding reviewers, and evaluating research impact). Additionally, many proofs of concept and announcements of upcoming tools were identified. Currently, however, there is a lack of research on the (real-life) performance of most of the identified tools, especially regarding their effectiveness, interoperability with other systems, or comparability with other (automated) tools or existing practices. Nevertheless, the potential changes to funding, research conduct and reporting that these tools (and their updates) might bring warrant timely stakeholder preparation, including financing of their piloting and further development.

Contents

Introduction

There are approximately 10 million researchers and 20 thousand research funders in the world today, with a global expenditure on Research and Development (R&D) amounting to 2.6% of Gross World Product (~2 trillion dollars), 60% of which is spent in the private business sector.[1-3] In the European Union (EU) this amounts to 1.9 million researchers, and 300 billion euros spent on R&D annually.[4] The overall research environment is soon expected to dramatically change with the advancements in artificial intelligence (AI), autonomous systems, robotics, and virtual environment systems (e.g. in Health Sciences, from 2010 to 2015 almost 30% of radiation diagnostic patents were AI related).[5] The AI field alone, currently publishes 60,000 publications per year and has seen a 12.9% annual increase in the last five years, with 12% of all arXiv preprints deposited in 2017 belonging to AI subject areas.[6]

On the other hand, sciences, especially Health Sciences, experienced a wake-up call in 2009 (reinforced in 2014 with an influential series of articles) about avoidable research waste amounting to up to 85% of all clinical research published, costing billions of Euros annually worldwide, and occurring largely due to avoidable research design flaws, non-publication of research, and unusable or non-replicable research.[7-10] In June 2017, the *Ensuring Value in* Research (EViR) funders' collaboration (which includes *The Netherlands Organisation for Health Research and Development* (Dutch: *De Nederlandse organisatie voor gezondheidsonderzoek en zorginnovatie, ZonMw*) as its founding member) culminated in publication of a consensus statement to ensure that the research funded by signatory members has justifiable research priorities; robust design, conduct and analyses; and includes complete information on research methods and findings from studies in order for research to be accessible, usable and replicable.[11] Additionally, ZonMw, together with *The Netherlands Organisation for Scientific Research* (Dutch: *Nederlandse Organisatie voor Wetenschappelijk Onderzoek, NWO*) also became signatories of *PlanS* which aims to accelerate transition to Open Access publications, for all publicly funded research in Europe,[12] and of *Findable, Accessible, Interoperable and Reusable* (FAIR) data principles aimed to ensure all research data is both human and machine usable.[13] Furthermore, ZonMw developed the *fostering Responsible Research Practices Framework* for planning, monitoring and evaluation of its programmes and projects.[14]

In light of the above, the *Open Science Committee* of ZonMw has commissioned this project to identify automation tools that could enhance funders' workflow and support funders in avoiding research waste, fostering responsible research practices and ensuring value in research, while at the same time stimulating ‘open science’ and research innovation.

Results and Discussion

Identified tools are presented per task they (aim to) automate or support. In Figure 1 we list those tasks and indicate where they fall in the simplified funder workflow (the detailed list of possible tasks and funder workflow steps is presented in the Appendix).

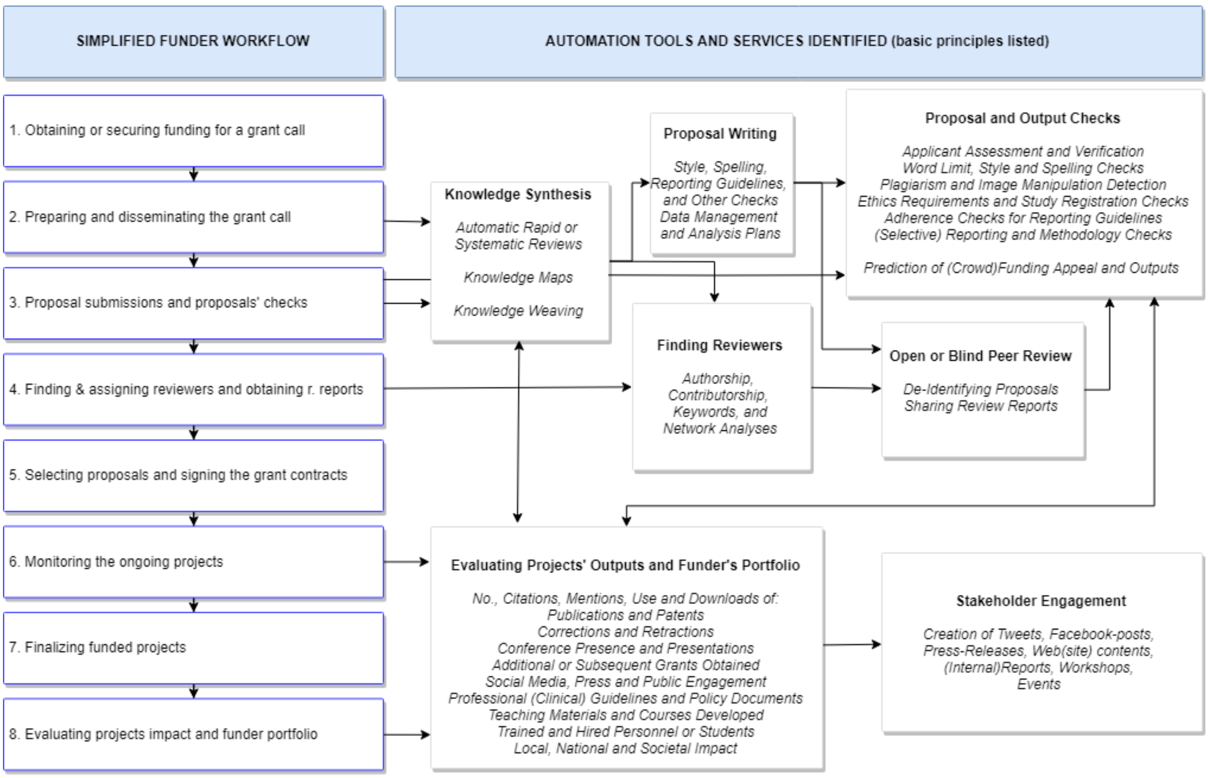

Figure 1. Simplified funder workflow.

Before describing the individual tools, it is important to highlight that in this report a tool is a software or a service (platform) developed to perform a specific task, independent of the mechanism (or algorithms) that enable it to do so. Therefore, a tool can actually consist of several different (AI) products all working together to perform one or more tasks, and it is very likely that many of the tools presented below may merge or serve as inspiration for development of new tools that are able to automate dozens of tasks. Furthermore, automation based on machine learning mechanisms most commonly depends on “training material” (i.e. the gold standard corpus consisting of correctly identified cases upon which the AI tool bases its algorithm for identifying and correctly labelling other cases - whether they are newly published, e.g. new scientific publications or grant applications, or belonging to historical or still unclassified records). However, even though considered a gold standard corpus, this training material often contains errors and biases, as the initial identification was almost always done by humans and can contain errors. This should be kept in mind when AI tools are evaluated by comparing their outputs to those produced by humans. Cases for traning can be anything: data, publications, authors, antibodies, model organisms, software, databases, services, questions, to real-word objects or any other information sources; and their numbers can be dazzling, e.g. there are currently 160 million scientific publications, with 3 million published every year, and growing.[1] They are also often largely unstandardized (e.g. references/citations formats are different between journals, and often contain errors due to manual insertions, misspells and differences in language translation).[15] Standardization processes require a lot of effort and resources and are nearly impossible to handle manually. Many identified papers in our scoping review cover means for improving standardization of processes and information extraction and are mentioned in their appropriate sections below. As classifications and identifications are evolving processes (e.g. scientific fields and subfields are often coded by funders, and grant calls made according to those classifications, but over time, those fields tend to change or diversify and previous grants and fields may require reclassifications) most solutions stress the importance of using systematized nomenclatures or codes, as well as standardized thesauruses and vocabularies, that bridge differences between scientific fields and languages. Examples include International Classification of Diseases (ICD), CRediT taxonomy for authorship contributions and Medical Subject Headings (MeSH) for indexation of publications in Health Sciences.

Furthermore, in (online) scholarly publishing, persistent identifiers have also emerged as optimal (machine-readable) solutions that allow for reliable identification of (unique) cases and ease of inter-operability with newly developed systems and tools (e.g. *ORCID IDs* for authors, *CrossRef Funder Registry* names for Funders, *Research Resource Identifiers (RRIDs)* for key biological resources, *Digital Object Identifiers (DOI)* for papers, data or projects, *PubMed Unique Identifiers (PMID)* for records within MEDLINE bibliographic database, *International Standard Serial Numbers (ISS*N*)* for journals, *Global Research Identifier Database (GRID)* for research institutions).

Stakeholders considering implementing any of the tools presented below, should first assess their workflows and estimate their return on investment, weighing the time and resources currently spent on specific tasks, time and resources need to train staff in the use of the tools, and determine (through pilot studies or simulations) gains achieved by supporting their current workflow steps with those tools. Furthermore, all tools we identified still require input from individual users, also require users to make decisions based on those outputs. These tools are also very likely to receive significant updates in the (very) near future, with high probability that these updates will include additional AI tools that will learn from how users handle the information the tools currently present. Furthermore, by learning from those decisions, the updated tools will be able to recommend responses and decision to users or automatically execute (at least a part of) those decisions. Finally, in the two workshops we held with stakeholders, we documented both excitement about the existing tools and those that may soon be developed, as well as worries regarding the responsibility that comes with trusting fully or semi-automated systems. In addition, we explored the impact such tools might have on innovation and freedom of pursuing research of interest to researchers themselves (detailed feedback is presented in the *Details of the Workshops* section).

Automation of Knowledge Synthesis

For many years researchers have been summarizing the evidence collected on scientific fields or specific topics in narrative, or more recently, systematic or scoping reviews, aiming to capture all the research familiar or discoverable to them through searches of bibliographic databases, grey literature and using accumulated prior knowledge and publications. With the steady increase in the number of new publications per year, the task of summarizing research has become increasingly difficult. Furthermore, it takes on average 2 years to conduct and publish a systematic review. Recently, however, knowledge synthesis has been enhanced through the use of bibliometric and systematic mapping enhanced by visual representations, which in their 2018 paper, Namakwa et al., term ***Research Weaving*** (Figure 2).[16]

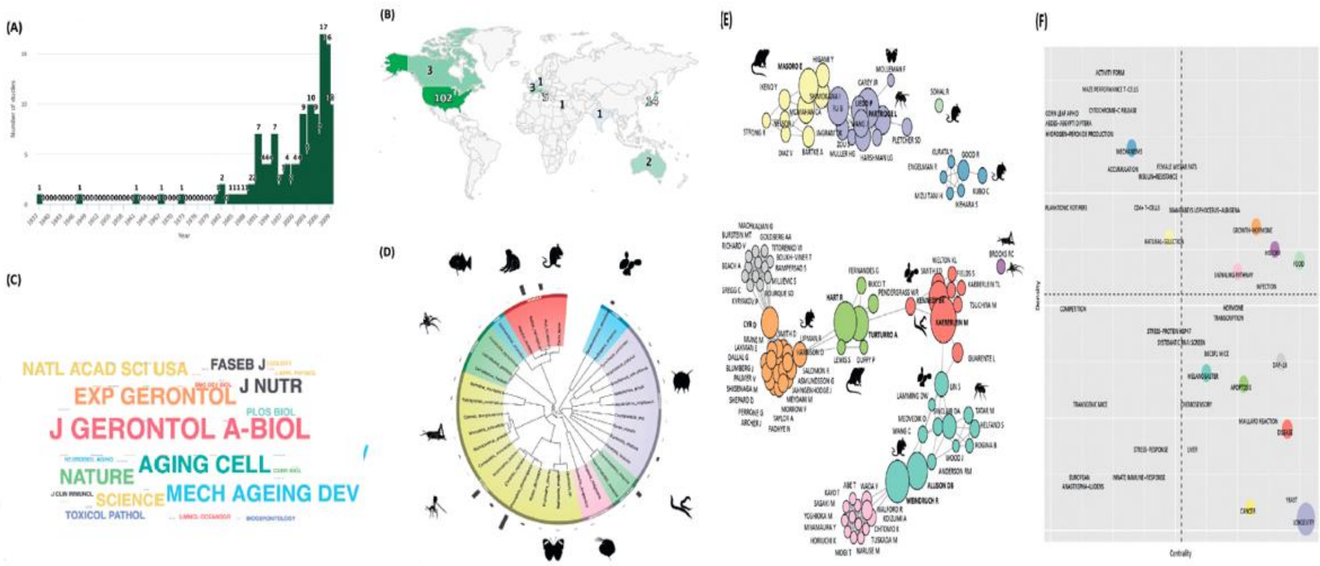

Figure 2. (Adapted from [16]). Example Visualizations for the Meta-analysis on the Relationship between Dietary Restriction and Longevity. (A) Distribution of publication dates of included studies, indicating a recent increase in number of published relevant studies. (B) Geographic distribution of the countries of origin of the first author of the included studies. (C) Word cloud of the publication journal names of the included studies. (D) Phylogenetic tree and representation of the main taxonomic groups of the species present in the meta-analytical dataset (bars show relative numbers of individuals of each species included in the analyses). (E) Author collaboration network, where nodes represent top 100 authors in terms of the numbers of authored papers in the data set; links are co-authorships; author clusters are manually annotated with the respective main study organisms. (F) Thematic map based on co-word network analysis and clustering of studies. More examples are available at www.example.researchweaving.com.

Similarly, in Health Sciences, the *Trip Database* has recently showcased its ***Evidence Maps,*** automatic evidence synthesis based on machine learning and natural language processing (Figure 3).

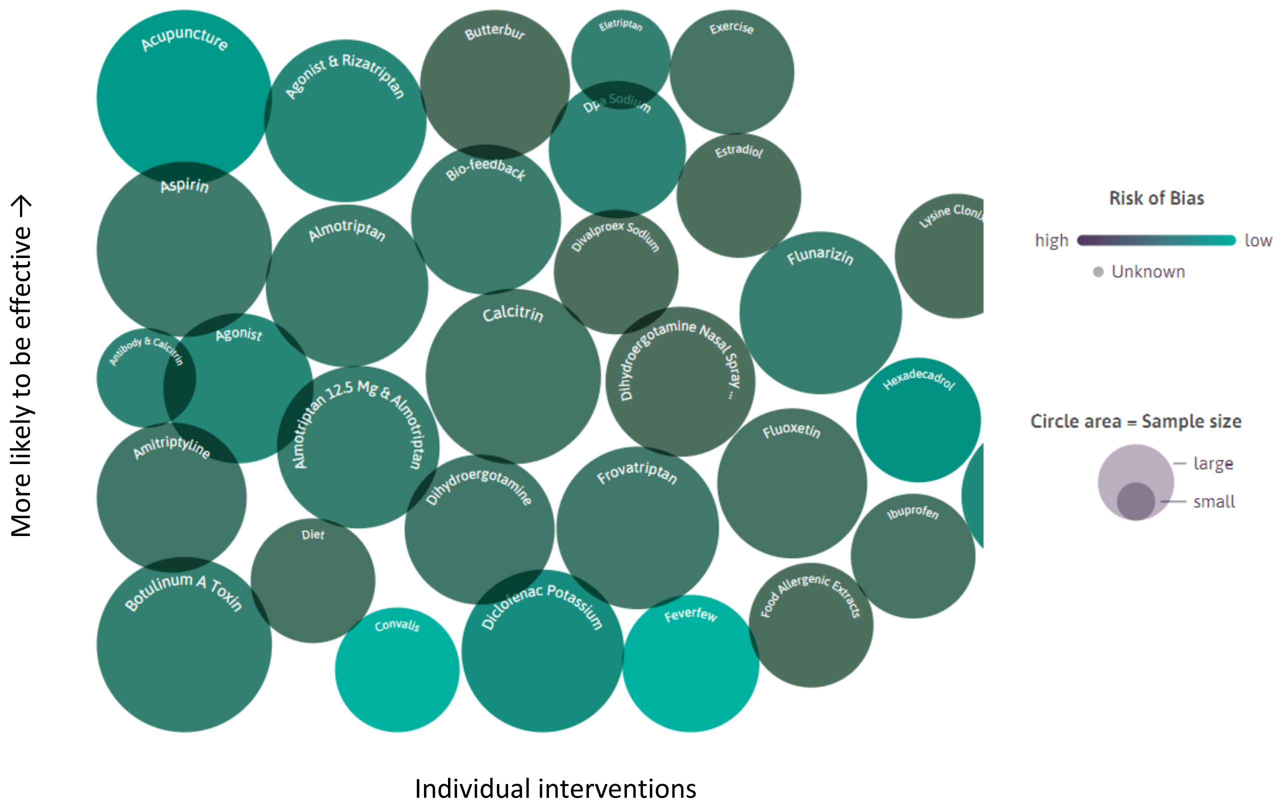

Figure 3. Automatic Evidence Map generated by Trip database on the interventions for Migraine based on 948 publications and displaying top 61 researched interventions.

Several papers we identified also described proofs of concept for creating metadata standards for clinical and translational research,[17] mining information from conferences or other websites usually not covered in bibliographic databases,[18] mining information from patents and publications to produce research trends,[19] determining knowledge landscapes and identifying research gaps,[20] predicting topic or field popularity and evolution, alongside funding distributions,[21-24] development of semantic search engines,[25] generating research maps,[26] as well as problems with automatic classification of search fields.[27, 28]

Besides the *Trip Database* mentioned above, our search has identified 7 tools which aim to automate synthesis or visualization of research, mostly based on processes mentioned before: bibliographic mapping, machine learning and natural language processing (Table 1). Most of these tools are still under development and have announced additional services they will be able to provide in the future. For example, *WizdomAI* states it will provide researchers with personal research graphs of publications, citations and grants in the context of global emerging trends; compare research output at a regional, national or global level to analyse research competitiveness; and analyse submitted grants, provide global publication trends, citation activities, and suggest potential reviewers.

Some of these tools incorporate information obtained through existing bibliographic databases or search engines that crawl content from many different sources like *Google Scholar, Dimensions, Microsoft Academic, OSF Search or Semantic Scholar.*[29] However, it is very likely that these tools may soon also incorporate raw data and metadata discoverable by search engines like Google's *Dataset Search*, Elsevier's *DataSearch*, *DataCite or Scholexplorer*. Furthermore, they may provide (real-time) alerts to users or funders on outputs they are interested in (see *Evaluating Projects' Impacts and Funder's Portfolio* section), suggest experts for research collaboration or review tasks, and possibly even the number and the availability of researchers that could apply for planned grant calls.

Over the last 4 years, the *International Collaboration for the Automation of Systematic Reviews (ICASR)* has held annual meetings and worked on gathering, testing and developing tools for accelerating steps in the creation of systematic reviews (currently over 150 tools are available at *the Systematic Review Toolbox website*).[30-32]

Table 1. Tools and services for knowledge synthesis.

Tool (link)	Area Coverage	Free Use	Short Description
Epistemonikos	Health Sciences	Free	Database of systematic reviews and research relevant for health-decision making.
CiteSpace	All Sciences	Free	Visualization and pattern analysis tool for constructing bibliometric networks and identifying hot topics and emerging trends.
Open Knowledge Maps	All Sciences or Health Sciences	Free	Visualization tool for displaying 100(+) most relevant papers on a topic from PubMed or BASE.
FederalREPORTER	All Sciences	Free	Database of grants and projects awarded by USA National Funding Agencies
SciCrunch	Health Sciences	Free	Data sharing, search and display platform. Allows generation of reproducibility reports for NIH grants.
Trip Database	Health Sciences	Free /Premium	Clinical evidence search-engine and evidence synthesis map generator.
VosViewer	All Sciences	Free	Visualization tool for constructing bibliometric networks and term co-occurrence networks.
WizdomAI	All Sciences	Free /Premium	Research intelligence services and visualization generation of research and funders outputs.

Recommendations on the use of the tools aimed at automatic knowledge synthesis: Currently the Trip Database's Automatic Evidence Map website states: "*This is a beta 'proof of concept' of a fully automated evidence mapping system. It is experimental and therefore the results should be dealt with appropriate scepticism*". Those aiming to use the tools listed above (e.g. funders investigating or refining the topic considered for funding, researchers generating introduction sections for their proposals or manuscripts, or reviewers checking researchers claims), should heed the same warning until robust evidence has demonstrated superiority or non-inferiority of those tools over current methods.

Writing Proposals or Publications

While our review primarily focusses on tools for funders, in Table 2 we list existing tools that funders might want to recommend to applicants writing their grant proposals or publications. Additionally, we present 2 tools that have recently been announced: *UNSILO*, which aims to evaluate manuscripts on their format and style requirements, provide word, phrases, sentences, and related manuscripts suggestions, and check for conflicts of interest and ethics requirements; [33, 34] and an *Add-on for MS Word*, which aims to help researchers adhere to reporting guidelines while writing manuscripts, specifically to *CONSORT, PRISMA, and STROBE* (abbreviations are expanded in the legend of Table 2).[35]

An excellent source of tools specifically aimed for researchers is also available as a crowdsourced database of *Tools and Innovations in Scholarly Communication* (currently listing more than 400 tools). Tools that could be used after proposals or publications have been written are described in the *Pre-Review Checks* sections below.

Lastly, the earliest tools aimed at researchers identified in our literature search were *GrantLearner* (1997), which notified individuals of new research grant opportunities that meet the learned profile of the individual's research interests,[36] and *GrantSlam* software (1999) which helped applicants not disrupt the page and table margins of *National Institutes of Health (NIH)* grant templates after filling them out and producing printouts.[37] Additionally, publications have described proofs of concepts for: automatic financial data capture and writing of grant financial statements for European Social Funds grants in Romania,[38] automating statistical analyses based on big data,[39] predicting crowdfunding success for start-ups,[40] and extracting reproducibility metadata (study methods, study tools, study data) from Health Sciences publications.[41] Furthermore, researchers have emphasized that many aspects of the proposal change in its writing stage, and therefore tools, templates or online submission systems, should include services which could automatically update parts of proposals affected by the made change (e.g. changes in number of deliverables or work packages may change the number of rows/columns of Gantt charts or similar tables and sections), and in that way help in reducing errors and decreasing the time needed for proposal preparation.[42]

Table 2. Tools and services for proposal or publication writing.

Tool (link)	Area Coverage	Free Use	Short Description
COBWEB	Health Sciences	Free	Research writing tool to help address all CONSORT items in the manuscript.
dkNET Reproducibility Report	Health Sciences	Free	Generation of reproducibility reports which ensure the identity and validity of key biological and/or chemical resources for NIH grants.
DMP Tool	All Sciences	Free	Application for creating data management plans that meet institutional and funder requirements.
ODM Data Analysis	Health Sciences	Free	Automatically generates generic descriptive statistics for each data item contained in an operational data model standard file.
PaperRater	All Sciences	Free	Writing tool that checks style, grammar, and conducts plagiarism checks.
PenelopeAI	All Sciences	Free /Premium	Ensures manuscripts meet journal requirements (conflicts of interest, ethics statements, citation style, formatting, captions, etc.)
StatReviewer	All Sciences	Premium	Checks that manuscripts follow appropriate reporting (ARRIVE, CONSORT, STROBE, STARD) or ICMJE guidelines and style.
The Experimental Design Assistant (EDA)	Health Sciences	Free	Application for designing animal research studies, recommending statistical plans, sample size calculation and support for randomization and blinding.
Worktribe	All Sciences	Premium	Platform that enables finding research collaborators, creation of management plans, contracts, research profiles and gathering of outputs.

Abbreviations: ARRIVE - Animal Research: Reporting of In Vivo Experiments; ICMJE - The International Committee of Medical Journal Editors Uniform Requirement for Manuscripts; CONSORT - The Consolidated Standards of Reporting Trials Statement; PRISMA - Preferred Reporting Items for Systematic Reviews and Meta-Analyses; STARD - Standards for Reporting of Diagnostic Accuracy Studies; STROBE - Strengthening the Reporting of Observational studies in Epidemiology.

Recommendations on the use of the tools for proposal or publication writing:

Despite the lack of research regarding effectiveness of most of these tools, funders should educate researchers about their development and (proposed) capabilities. Additionally, funders should ask for (or integrate into their systems) declarations on use of such tools during proposal or manuscript submission, and consider funding or piloting studies that evaluate if use of such tools leads to better (or worse) proposals or manuscripts.

Proposals' or Manuscripts' Pre-Review Checks

Like scientific journals, most funders today use online submission systems for grant proposals, requiring users to create an account or use (inter)national or institutional identifiers to confirm their identity. Then users fill out designated forms or upload the proposal and associated documentation, which often includes detailed information on principal investigators as well as institutional or independent guarantees or approvals required for conducting the research (e.g. ethics approvals, data management plans, laboratory or equipment specifications). Large variations exist between requirements and forms used by different funders, including on the availability of submission templates, and having one or two rounds of the process (e.g. first short and the second detailed proposal submission and review). Writing and submitting proposals often requires significant time investments, and many interventions surrounding these processes that do not even require automated tools have recently been described in a systematic review of innovations for effectiveness and efficiency of health funded research (e.g. shortening of required proposal documentation and word limit, with implementing journal like peer review system lead to significant cost reduction for the *National Health and Medical Research Council* of Australia).[43] Additionally, awareness that much of the information required by funders requires regular updating (e.g. CVs of applicants), proposals have been made to reduce the time needed for constant updates of such documents and to increase the trustworthiness of by using (semi-)automated services.[44-46] For example, recently *ORCID's Reducing Burden and Improving Transparency (ORBIT)* project proposed confirming the applicants' identity and other information required through the use of ORCID iDs.[47] It is foreseeable that similar services, such as the recent expansion of researchers *Publons (reviewer contribution)* profiles to include researchers' publications and citations with the ability to export verified CVs[48] will become the new standard. We expect that many of the current researchers profile and ID systems such as *ScopusID*, *ResearchGate profile, Kudos profile, EU expert profile, ResearcherID*) will start providing similar services, including descriptions of exact authorship contributions (e.g. CRediT or CRO taxonomy),[49-51] attendance at presentations at conferences, teaching and many additional indicators (see *section* *Evaluating Projects' Impacts and Funder's Portfolio*). Furthermore, as development of identification for other devices and services is moving beyond the use of usernames and passwords (i.e. use of pin codes, fingertips, eye or face recognition), similar identification technologies may also overtake the current identification methods in scholarly communication, and require implementation by funders.

A detailed list of tasks that may be conducted as part of proposal pre-review checks is presented in the Funder Workflow section. In table 3 we list identified tools for automating some of those tasks. Additionally, our search revealed proofs of concepts for automatic detection of errors when *Hazard Ratios, Odds Ratios, and Relative Risks* are reported in MEDLINE indexed papers,[52] creation of an *R-factor*, a proposed numerical index for predicting veracity of publications,[53] and calculation of relevance and focus shift indexes which could indicate how well the proposals (mis)align with previous research of appplicants.[54, 55] Finally, on 20 December 2018, *Wellcome Trust* issued a request for information regarding *FAIRware* tools to assess the research outputs against a structured checklist of requirements aligned with FAIR principles. Information obtained is expected to be shared by the end of March 2019, with possible request for procurement from the Wellcome Trust being issued in the second quarter of the year.[56]

Note: Because there are currently more than 30 different tools for plagiarism detection,[57] novel ways of plagiarism detection being proposed that are not based on text-similarity,[58] developments in image manipulation or detection of improper use of images,[59-63] and the fact that most of tools were not designed for (rejected) grant proposals (which are also usually not freely available documents), we decided not to include those tools in this scoping review.

Table 3. Tools and services for conducting pre-review checks of proposals or manuscripts.

Tool (link)	Area Coverage	Free Use	Short Description
ADA (by Editage)	All Sciences	Premium	Checks submitted manuscripts for writing quality and ethics requirements; can be integrated with iThenthicate.
AIRA (Artificial Intelligence Review Assistant)	All Sciences	Premium	Checks submitted manuscripts for writing quality and ethics requirements; can be integrated with iThenthicate and ADA. Suggests reviewers, checks conflicts of interest of authors, reviewers and editors.
PageMajik	All Sciences	Premium	Checks manuscripts or books for style, reference and proofreading errors. Enables book design.
PenelopeAI	All Sciences	Free /Premium	Ensures manuscripts meet journal requirements (conflicts of interest, ethics statements, citation style, formatting, captions, etc.)
Retraction Watch Database	All Sciences	Free	Largest database of known retracted publications, allows

			checking if applicants, experts or reviewers had any retracted papers and lists reasons for the retractions.
StatCheck	All Sciences	Free	Check manuscripts for errors in statistical reporting (requires APA style statistical reporting).
StatReviewer	All Sciences	Premium	Check manuscripts follow appropriate reporting (ARRIVE, CONSORT, STROBE, STARD) or ICMJE guidelines and style.

Recommendations on the use of the tools for conducting pre-review checks of proposals or manuscripts: Currently, evidence on real-world effectiveness of the tools described in this section is lacking. Nevertheless, automatic screening of proposals and manuscripts shows great potential for ensuring value in research, and could lead to changes in the way research is designed and conducted, especially if researchers are confronted with the fact that these checks will be made on all the proposals or research they submit. Funders should also consider joining ORCID's ORBIT initiative to synchronize, reduce burden and speed up the exchange of information between stakeholders.

Finding Reviewers and Reviewing Proposals

The mechanisms that are used in automation of knowledge synthesis (bibliometric , systematic and AI mapping of publications, conferences, institutional and individual researcher websites, and other sources)[64, 65] can also be employed for finding suitable reviewers to assess the quality, rigor, innovativeness or feasibility of research proposals. Additional proofs of concept for these tasks have been demonstrated for applying different weights for collected outputs (e.g. citations and collaboration analyses),[66] for algorithms that suggest and allocate potential reviewers according to the total number of received proposals and reduce burden for individual reviewers,[67, 68] for reviewer suggestions based on abstract keywords matching,[69] and creating census of researchers by scraping institutional websites.[70]

Identified tools that may help funders find potential reviewers are listed in table 4. Additionally, *UNSILO*, (described also in the *Knowledge Synthesis* section) has also been announced as a tool for finding potential reviewers. Lastly, giving credit to reviewers of proposals is very likely to become more prominent (as well as standardized and verified), as has happened to manuscript reviewing credit currently provided by *Publons* or large publishers (e.g. *Elsevier's Reviewer Recognition Platform*).[71]

Table 4. Tools and services for finding reviewers.

Tool (link)	Area Coverage	Free Use	Short Description
AIRA (Artificial Intelligence Review Assistant)	All Sciences	Premium	Checks submitted manuscripts for writing quality and ethics requirements; can be integrated with iThenthicate and ADA. Suggests reviewers and checks conflicts of interest of authors, reviewers and editors.
Anne O'Tate	Health Sciences	Free	Identifies the top authors associated with a PubMed search query. Provides an overview of articles associated with the query.
Elsevier's Expert Lookup	All Sciences	Premium	Suggests experts based on natural language processing of the Scopus database.
Journal/Author Name Estimator (JANE)	Health Sciences	Free	Identifies reviewers, journals and citations that are associated with a PubMed search query.
Publons	All Sciences	Free	Database which enables gathering and searching for individuals' publications, citation metrics, verified peer review and editor experience.
PubReMiner	Health Sciences	Free	Identifies the top ranked authors associated with a PubMed search query. Provides an overview of research interests, and journals were most of publications related to the query are published.
Reviewer Finder (Dimensions)	All Sciences	Premium	Identifies experts using natural language processing of grants and publications. Part of Dimensions for Funders.
Reviewer Finder (Springer Nature)	All Sciences	Springer-Nature Editors Only	Compares manuscript submissions against Nature database of experts and their publications.
Reviewer Locator (Clarivate)	All Sciences	Premium	Compares manuscript submissions against Web of Science Core Collection content to generate a list of experts as potential reviewers (integrated with Scholar One).
VosViewer	All Sciences	Free	Visualization tool for constructing bibliometric networks and term co-occurrence networks.
WizdomAI	All Sciences	Free /Premium	Research intelligence services and visualization generation of research and funders outputs.

Finding reviewers, especially those available for the required period of evaluation, is becoming increasingly difficult.[71] Additionally, funders also have to decide on many other review processes, including: the number of reviewers they will use per proposal; the use of (additional) methodological, statistical or ethics reviewers; (dis)allowing reviewers to vote which proposals they would like to evaluate, the need for (in-person or remote) reviewing, (final) scoring mechanism; adjusting reviewer scores based on their previous (stricter or lenient) performance; use of consensus reports; applying open or (double) blind reviewing; and deciding if any or all of the proposals can be resubmitted and amended based on reviewer comments.

Our search strategy has captured several publications dealing with the problems and solutions for automatic de-identification of documents,[72-77] however as automatic de-identification is almost never used by funders (or by journals, who predominantly ask authors to remove all identifying information from their manuscripts) we chose not to list those tools or proofs of concept.

Finally, many of the tools listed for pre-review checks could ensure that reviewers do not need to spend time on detecting at least those aspects that could be checked automatically. We have, however, not identified any tools aimed at assessing the quality of the reviews themselves or those aimed at substituting reviewers altogether. It is, nevertheless, highly probable, with the recent publication of a systematic review on non-automated tools (checklists and scales) to assess the quality of reviews in Health Sciences publications,[78] coupled with the development of AI tools for reporting guidelines adherence, that review adherence tools based on those checklists will also be developed.

Recommendations on the use of the tools for finding reviewers:

Currently, firm evidence is lacking on performance of tools for finding reviewers compared to using previous lists or following suggestions by other reviewers or applicants. We think, however, that due to the ease of use of these tools and their underlying principles, funders, editors and conference organizers should be transparent when they employ them. Furthermore, they should consider conducting or funding studies that compare different reviewer suggestion strategies or tools bearing in mind that due to rapid updates of these tools regular evidence updates may be needed. Finally, funders should incorporate or enable services which provide credit recognition for their reviewers and enable sharing of verified credit with other stakeholders.

Evaluating Projects' Impacts and Funder's Portfolio

Measuring of research impact has received significant attention over the last decades, with more than 50 different indicators being used in Health Sciences, covering, among others, research activity through bibliometrics (e.g. publications and their citations, corrections and retractions), collaboration networks (both national and international), (social) media impact, societal impact (e.g. industrial, cultural, legal, behavioural, and health impact), stakeholder engagement, and educational outcomes (e.g. courses designed, students and personnel trained).[79] It has also been met with criticism, as reducing the research milieu to indicators (i.e. numbers) usually fails to account for many of the inequalities, hype, time and resources available when working in a specific research environment.[80] These indicators may also require different adjustments for different goals by weighing some dimensions more than others, and can be unable to capture every specific research situation. For example, if two scientists collaborating on a project decide to publish their results separately, co-authorship analysis will not detect such collaboration. In addition, opinions regarding the importance of individual indicators and their relative weights may differ between stakeholders. In the past, relying on too many indicators had proven to be costly, and even providing little to no additional gain instead of using just a few.[81] Nevertheless, indicators are often used for initial screening or supporting the selection of job candidates, students for enrolment at university programs, tenure promotions as part of investigator assessment for grant proposals, and overall portfolio assessment of funders. A reform of the research assessment processes had gained momentum with the 2012 *San Francisco Declaration on Research Assessment (DORA)*,[82] and in 2019 the Dutch funding and research institutions published a statement seeking to renew national frameworks for scholarly recognition and assessment.[83] With the recent developments in knowledge synthesis, standardization of nomenclatures and identifiers such as ORCID ID, (open) sharing of citation information and other open science initiatives, (automatic) collection of many of the indicators is becoming easier and cheaper.[84] In table 5 we list the identified tools for their collection. Additionally, we identified proofs of concept describing: extraction of information from acknowledgments, funding or affiliation sections,[85-92] extraction of indicators from publications, policies, regulations, clinical guidelines, or expert panel reports,[93-96] including from non-English language outputs,[97, 98] extraction and curation of references for digital humanities books, articles and blogs,[99, 100] extraction of collaboration indicators based on links between websites of institutions,[101] automatic standardization of publications, reagents, patent, software or grants for later information retrieval,[102-110] and comparison of performance between different funders,[111] researchers or labs. [112, 113]

Table 5. Tools and services for evaluating projects' impact and funder's portfolio.

Tool (link)	Area Coverage	Free Use	Short Description
Altmetrics Explorer for Funders	All Sciences	Premium	Measures influence each project achieves across the mainstream media, on social and community platforms, and in the formation of public policy.
CHORUS Clearinghouse	All Sciences	Free	Measures public access availability, re-use licences, preservation on dark archives, use of ORCID IDs and links to funders on project websites. Enables data storage and discoverability.
CrossRef Funder Search	All Sciences	Free	Provides information on outputs that used Crossref funder ID.
EU-TrialTracker FDA-TrialTracker	Health Sciences	Free	Provides information on published results of clinical trials per funder.

Recommendations on the use of the tools for collection of research indicators:

A large corpus of literature exists on the (mis)use of indicators for research evaluation and personnel selection or advancement. Funders should be transparent if and which tools they use that automatically collect such indicators, and they should provide information on how individual indicators will influence their decisions (while being careful not to promote indicator accumulation instead of excellence in research). Currently, *TrialTracker* (for funders sponsoring clinical trials) and *CHORUS Clearinghouse Dashboard Service*, and if developed *FAIRware tool (mentioned in Pre-Review Checks)*, have high potential for demonstrating and alerting funders when outputs created by projects they funded are (mis)aligned with their policies and agendas. Additionally, for reducing non-publication of research (results), funders should consider following the example of *National Institute for Health Research* in the UK, which has implemented a concept of living threaded publication where all stages of the projects development and outputs are reported on the funder's website and all publications arising from funded projects are required to be published in journals set up and run by the funder (Figure 4).[114]

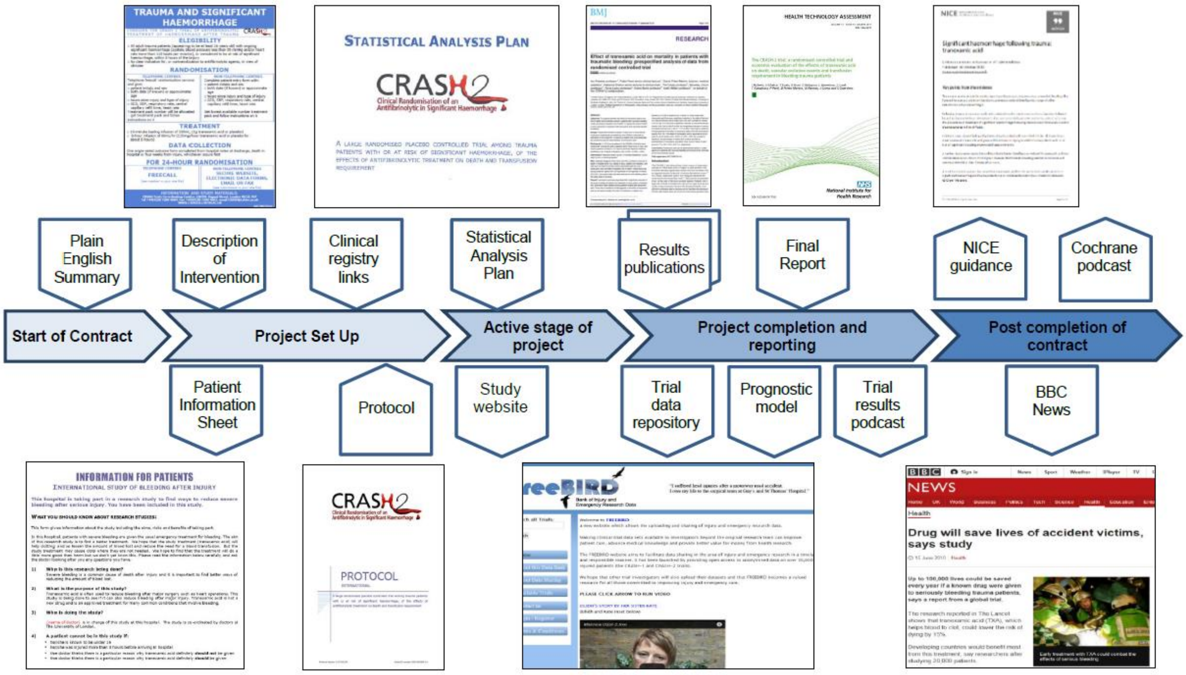

Figure 4. Example of thread of information for one funded project (CRASH2 trial) in the National Institute for Health Research Journals Library.[114]

Stakeholder Engagement and Resource Management

Our review has focused on tools that could enhance the funder's workflow and support funders in avoiding research waste, fostering responsible research practices and ensuring value in research. Our search results also included some services, tools or proofs of concept which aim to help with resource, personnel and content management,[115, 116] calendar scheduling,[117] accounting and record holding, automatic generation of (social) media outputs, creation of questionnaires,[118] frequently asked questions sections, support services, and many other businesses or organization functions, but those go beyond the scope of our review. Use of such tools, should in principle follow the same testing and avoid the same caveats as those we mentioned above. Additionally, generation and (open) sharing of detailed funder workflows by funders could foster collaboration between funders and identify steps where such tools are lacking or might be particularly valuable,[119] potentially leading to grant calls dedicated to their development.

Final Recommendations for Funders

Almost all of the existing tools and services listed above currently lack sufficient evidence for their effectiveness, and the ease of their integration or adaptation with existing funders workflows, as well as the benefits that could be gained from their use, still need to be investigated. Nevertheless, it is very probable that research aimed at demonstrating their effectiveness and integration or adaptation will soon commence or that the results of currently ongoing testing will soon be published. We would therefore recommend funders devise specific calls aimed specifically at development or adaptation of automated tools, as well as testing or piloting the use of currently existing tools, as these tools have the potential for drastically enhancing the current workflows, helping avoid research waste, fostering responsible research practices and ensuring value in research, with possibly even changing and optimizing the way research itself is conducted and reported.

Furthermore, we strongly feel that funders should join the ORCID's ORBIT initiative[47] or adapt their systems in a way that would allow applicants and reviewers to share all the information funders require from them through that log in (and similarly provide all information on their co-applicants by providing their ORCID, Publons or similar iDs) and thus reduce a least of portion of the time burden currently required in grant applications. Especially, in light of the current developments in automatic gathering of different metrics described in detail in the *Evaluation Section*.

Funders should also provide verified credit recognition for reviewers they employ, and share that recognition with existing services such as ORCID or Publons, or collaborate with other funders or services (i.e. EU expert portal services) for sharing of this information. Similarly, funders (alone or as a consortium) should implement standards and meta-data for grant calls and funded proposals that would allow other funders or researchers to more easily search and be aware of the global funding milieu, and in that way help reduce possible misuse of the granting processes (e.g. plagiarism of ideas and proposals, or duplicate applications of the same research to different funders).

Additionally, funders should join the CHORUS or Altmetric monitoring of their outputs or solicit provision of collection of those and similar vital indicators to guarantee that their values are being followed by the researcher they fund. Solicited, CHORUS, Altmetric, or TrialTracker outputs (for funders that fund clinical trials) should also be integrated and displayed on the funder's websites, and used in stakeholder outreach to both promote the transparency of funder's work as well as to serve as guarantees for the value in reducing the waste of the research they fund.

Funders should also consider experimenting with reducing the length of their current application requirements or embracing a more journal like peer review process, as described in the recently published systematic review of innovations for effectiveness and efficiency of health funded research.[43]

Finally, in order to reduce research waste, prevent non-publication of undertaken research, and promote transparency of the research projects (e.g. documentation of possible outcome changes or deviations from study protocols or inceptions), we encourage funders to share accepted research proposals, as well as all protocols and changes to those protocols for research they fund, by either mandating their deposit on existing project or preprint servers (e.g. OSF, Mendeley) or by investing in services that would allow funders to host and share them on their own websites or services (as exemplified by the *National Institute for Health Research in the UK).*[114]

A brief schematic of these and recommendations mentioned in above sections are presented below in Figure 5.

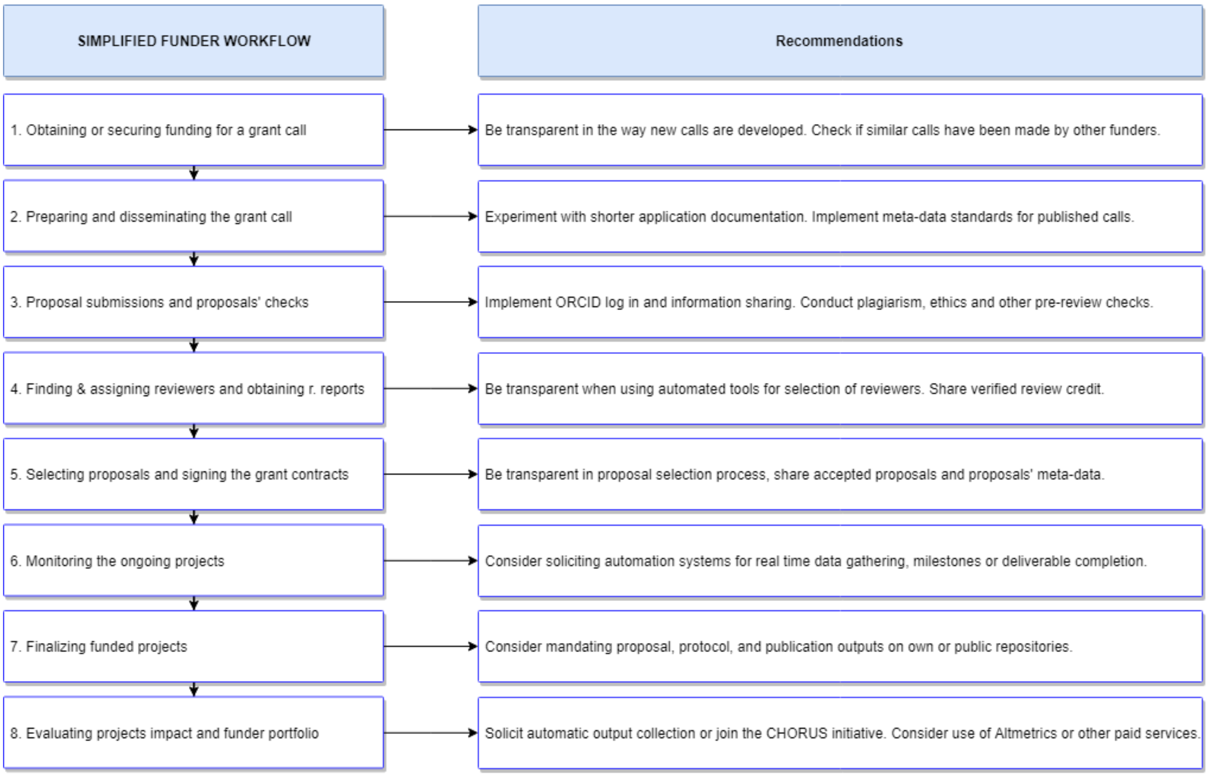

Figure 5. Recommendations for funders considering using automated tools to enhance their workflows.

Methods

This project started on 1 June 2018 and ended on 28 February 2019. It consisted of a scoping review of scientific databases and grey literature which aimed to identify existing or upcoming automation tools that could be used by funders. In addition, two stakeholder workshops (one invitational, held at 29 January 2019, and the other held as a part of *Researcher to Reader* 2019 conference in London, 26-27 February) were held where the pros and cons of the tools and their possible impact were discussed. In order to be able to identify appropriate tools, we first attempted to map (potential) funder workflow steps (presented below) to be able to align the tools with those steps. Funder workflow was constructed based on internet search or major funder websites (*EU Commision*, *ZonMw*, *Welcome Trust*, *NIH*), personal experiences, and based on consolations with stakeholders and *ZonMw* employees. Additionally, project team members met every 6 weeks to discuss and plan the project's activities.

Details of the Scoping Review

We searched 4 scientific bibliographic databases: Web of Science (WoS), Scopus, MEDLINE and the DBLP Computer Science Bibliography on 2 November 2018 (search strategy for each database available in the appendix), obtaining 2207, 1843, 1105, an 413 results, respectively, which we exported to Rayyan Software (https://rayyan.qcri.org/) and following manual de-duplication, we screened 4563 records for inclusion. Initial selection led to 126 publications, for which we obtained full text, and subsequently we included 84 publications.

Search of grey literature included: *Google Scholar* search, *Scholarly Kitchen* posts (https://scholarlykitchen.sspnet.org/), crowdsourced database of *Tools and Innovations in Scholarly Communication* consisting of over 400 tools, *Twitter* posts, personal communication, *Elsevier Connect* posts (https://www.elsevier.com/connect), and the *Systematic Review Toolbox* catalogue of tools supporting automation of systematic reviews (http://systematicreviewtools.com/).

Details of the Workshops

We held two workshops to assess stakeholders' opinions about the tools, pros and cons of using them and ideas for the future. The workshops were:

1) Automation Tools Workshop – invitational 3-hour workshop held on 29 January 2019 at ZonMw, Den Haag, The Netherlands.
2) Automating Funders' and Researchers' Workflows Workshop – 3 sessions of 50 min each, held as a part of Researcher to Reader Conference in London, during 26 and 27 February 2019 (2 sessions were held on the 26, one on 27 February).

Feedback from the Workshops

Use of AI in Scholarly Communication and Publishing

Benefits: May speed up transition to open science practices, as open access papers provide easier access to training materials for AIs.

Concerns: High initial enthusiasm for AI, but maybe they will underperform and make researchers delay or give up on doing some research they initially were interested in. Privacy and data protection may be jeopardised. May lead to culture of blaming, profiling and not allowing errors to be corrected.

Unresolved Questions: It is unknown how much input or supervision tools will require from humans. It is unclear how and who will provide quality insurance for the tools, and responsibility when something goes wrong. Will AIs be able to solve problems where the corpus for their training is small? Who will train the researcher or users on their use as many of the products often don't have dedicated support (one solution offered was librarians)?

Knowledge Synthesis tools

Benefits: Decrease in time needed to conduct research synthesis, increase in efficiency, and coverage (of databases), reduction of bias, freeing up of researcher time that could be used to develop new skills. Could lead to better identification of emerging fields.

Concerns: Could make (systematic) reviews and researcher conducting them redundant. With increasing levels of abstraction, loss of information and additional biases may be introduced. It is not clear how the tools will handle duplications or differences in preprint and other versions of documents. Will proper attribution be given to sources who were used in knowledge synthesis, those used for training of the tools, or those used to develop best methods to conduct a study?

Pre and Post Publication or Proposal Checks

Benefits: Culture shift might occur if researchers know that their outputs will be checked by AIs. AIs could tag or extract sections of papers that are needed for replicating the study. Increase the quality of publications, decrease the number of errata and retractions, as well as time needed to conduct peer review.

Unresolved Questions: Who will develop standards on which checks are needed for each field? Once proven, should all previous publications be checked and could or should they be corrected accordingly?

Impact Measurement

Benefits: Automatic collection of many different impact measurements may allow customization of those needed for specific purposes (e.g. one set of indicators for teachers, other for researchers).

Concerns: That metrics do not adequality describe individuals and may be misused or even have unintended consequences or uses. As they provide shortcuts to assessments, it is possible users will want one indicator that covers all outputs, which could lead to information loss or gaming of the system. Who will develop proper weighting and normalization for different fields and backgrounds?

Limitations

While we have covered 4 large bibliographic databases, personal contacts and many social media resources, it is very probable we have missed some tools for optimizing workflows of funders that have been reported and published either on individual funders or company websites, or in scholarly articles without using the automation, artificial intelligence or machine learning terms. Furthermore, an extensive analysis of each of the listed tools and services was beyond the scope of this review, so it is possible we may have missed some aspects of the tools or information on functions that are still in development. Finally, while we have held two workshops with stakeholders surrounding the potential impact of these tools, we have not performed any of the testing or comparisons of the tools themselves, beyond trying the functions that were freely available to users till March 2019 (and most of which have been reported above).

Project Team Members

Note: Roles of members and project advisors are described using the CRediT taxonomy.[49]

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Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Visualization, Writing – Original Draft Preparation, Writing – Review & Editing

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Conceptualization, Funding Acquisition, Methodology, Project Administration, Supervision, Writing – Review & Editing

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All Committee Members contributed to: Conceptualization, Methodology, Supervision, Writing – Review & Editing.

Project Advisors

All project advisors contributed to Writing – Review & Editing.

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References

1. The STM Report: An overview of scientific and scholarly journal publishing. Hague, the Netherlands; 2018.
2. CrossRef Funding 2019 [Available from: https://search.crossref.org/funding.
3. OECD. OECD Science, Technology and Industry Scoreboard 20172017.
4. Europe 2020 indicators - R&D and innovation.
5. STI Micro-data Lab: Intellectual Property Database. In: OECD, editor. 2017. http://dx.doi.org/10.1787/888933617016.
6. Elsevier. ArtificiaI Intelligence: How knowledge is created, transferred, and used.: Elsevier; 2018.
7. Chalmers I, Glasziou P. Avoidable waste in the production and reporting of research evidence. The Lancet. 2009;374(9683):86-9.
8. Glasziou P, Altman DG, Bossuyt P, Boutron I, Clarke M, Julious S, et al. Reducing waste from incomplete or unusable reports of biomedical research. The Lancet. 2014;383(9913):267-76.
9. Macleod MR, Michie S, Roberts I, Dirnagl U, Chalmers I, Ioannidis JP, et al. Biomedical research: increasing value, reducing waste. The Lancet. 2014;383(9912):101-4.
10. Glasziou P, Macleod M, Chalmers I, Ioannidis JP, Salman RA-S, Chan A-W. Research: increasing value, reducing waste – Authors' reply. The Lancet. 2014;383(9923):1126-7.
11. Chinnery F, Dunham KM, van der Linden B, Westmore M, Whitlock E. Ensuring value in health-related research. The Lancet. 2018;391(10123):836-7.
12. cOAlition S: Making Open Access a Reality by 2020 [press release]. Science Europe2017.
13. Wilkinson MD, Dumontier M, Aalbersberg IJ, Appleton G, Axton M, Baak A, et al. The FAIR Guiding Principles for scientific data management and stewardship. Scientific Data. 2016;3:160018.
14. Reijmerink W. Strengthening Impact in The Netherlands: The case of ZonMw. ZonMw; 2018.
15. Guraya SY. Accuracy of references in scholarly journals: An analysis of 450 references in ten biomedical journals. European Science Editing. 2014;40(4):88-90.
16. Nakagawa S, Samarasinghe G, Haddaway NR, Westgate MJ, O'Dea RE, Noble DW, et al. Research weaving: visualizing the future of research synthesis. Trends in ecology & evolution. 2018.
17. Hume S, Chow A, Evans J, Malfait F, Chason J, Wold JD, et al. CDISC SHARE, a Global, Cloud-based Resource of Machine-Readable CDISC Standards for Clinical and Translational Research. AMIA Jt Summits Transl Sci Proc. 20172018. p. 94-103.
18. McEntire R, Szalkowski D, Butler J, Kuo MS, Chang M, Chang M, et al. Application of an automated natural language processing (NLP) workflow to enable federated search of external biomedical content in drug discovery and development. Drug Discovery Today. 2016;21(5):826-35.
19. Dey L, Mahajan D, Gupta H. Obtaining Technology Insights from Large and Heterogeneous Document Collections. Proceedings of the 2014 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT) - Volume 01. 2682779: IEEE Computer Society; 2014. p. 102-9.
20. Chan L, Stout NL, Alfano CM, Belter CW, Cernich A, Nitkin R, et al. A Bibliometric Analysis of the Landscape of Cancer Rehabilitation Research (1992–2016). JNCI: Journal of the National Cancer Institute. 2018;110(8):815-24.

21. Sobkowicz P. Utility, Impact, Fashion and Lobbying: An Agent-Based Model of the Funding and Epistemic Landscape of Research. Journal of Artificial Societies and Social Simulation. 2017;20(2):5.
22. Yanzhong D, Zhaoguo X, Li C, editors. The analysis of research fields of chinese natural science funds based on text classification. 2008 8th IEEE International Conference on Computer and Information Technology; 2008 8-11 July 2008.
23. He D, Parker DS, editors. Learning the Funding Momentum of Research Projects. Advances in Knowledge Discovery and Data Mining; 2011 2011//; Berlin, Heidelberg: Springer Berlin Heidelberg.
24. Kolahi J, Khazaei S. A scientific forecast on dental research output within the next 20 years using exponential smoothing algorithm. Dental Hypotheses. 2017;8(1):3-7.
25. Vasilateanu A, Goga N, Sutu T, Nastasescu M, Moldoveanu A, Asavei V, et al., editors. QUESTOR -- Automatic Searching for Reports. 2013 19th International Conference on Control Systems and Computer Science; 2013 29-31 May 2013.
26. Landreth A, Silva Alcino J. The Need for Research Maps to Navigate Published Work and Inform Experiment Planning. Neuron. 2013;79(3):411-5.
27. Bornmann L. Field classification of publications in Dimensions: a first case study testing its reliability and validity. Scientometrics. 2018;117(1):637-40.
28. Herzog C, Lunn BK. Response to the letter ‘Field classification of publications in Dimensions: a first case study testing its reliability and validity’. Scientometrics. 2018;117(1):641-5.
29. Gusenbauer M. Google Scholar to overshadow them all? Comparing the sizes of 12 academic search engines and bibliographic databases. Scientometrics. 2019:1-38.
30. Beller E, Clark J, Tsafnat G, Adams C, Diehl H, Lund H, et al. Making progress with the automation of systematic reviews: principles of the International Collaboration for the Automation of Systematic Reviews (ICASR). Systematic reviews. 2018;7(1):77.
31. O’Connor AM, Tsafnat G, Gilbert SB, Thayer KA, Wolfe MS. Moving toward the automation of the systematic review process: a summary of discussions at the second meeting of International Collaboration for the Automation of Systematic Reviews (ICASR). Systematic reviews. 2018;7(1):3.
32. O’Connor AM, Tsafnat G, Gilbert SB, Thayer KA, Shemilt I, Thomas J, et al. Still moving toward automation of the systematic review process: a summary of discussions at the third meeting of the International Collaboration for Automation of Systematic Reviews (ICASR). Systematic reviews. 2019;8(1):57.
33. UNSILO. UNSILO 2019 [Available from: https://site.unsilo.com/site/unsilo-manuscript-evaluation/.
34. Clarivate. Clarivate Analytics and UNSILO partner to power ScholarOne with AI2018. Available from: https://clarivate.com/blog/news/clarivate-analytics-and-unsilo-partner-to-power-scholarone-with-ai/.
35. Hawwash D, Lachat C, De Cock N, Kolsteren P. Integrating a writing aid to facilitate the use of reporting guidelines: a crossover randomized controlled trial: trial protocol. 2018.
36. Ackerman M, Billsus D, Gaffney S, Khoo G, Hettich S, Kim DJ, et al. Learning probabilistic user profiles: Applications for finding interesting web sites, notifying users of relevant changes to web pages, and locating grant opportunities. AI magazine. 1997;18(2):47.
37. Schutzer S. GrantSlam: Automation of the Public Health Service Grant Application Process. Jama: The Journal of the American Medical Association. 1999;282(19):1878-9.
38. Mihăilă A, Benţa D, Rusu L. Framework for Automated Reporting in EU funded Projects. International Journal of Computers Communications & Control. 2014;9(6):721-9.
39. Behnaz A, Rabhi F, Peat M, editors. A Software Architecture for Enabling Statistical Learning on Big Data. International Work-Conference on Time Series Analysis; 2016: Springer.

40. Zhang Q, Ye T, Essaidi M, Agarwal S, Liu V, Loo BT, editors. Predicting startup crowdfunding success through longitudinal social engagement analysis. Proceedings of the 2017 ACM on Conference on Information and Knowledge Management; 2017: ACM.
41. Valdez J, Kim M, Rueschman M, Socrates V, Redline S, Sahoo SS, editors. ProvCaRe semantic provenance knowledgebase: evaluating scientific reproducibility of research studies. AMIA Annual Symposium Proceedings; 2017: American Medical Informatics Association.
42. Kolovos DS, Matragkas N, Williams JR, Paige RF, editors. Model driven grant proposal engineering. International Conference on Model Driven Engineering Languages and Systems; 2014: Springer.
43. Shepherd J, Frampton GK, Pickett K, Wyatt JC. Peer review of health research funding proposals: A systematic map and systematic review of innovations for effectiveness and efficiency. PloS one. 2018;13(5):e0196914.
44. Garcia CM, Pereira AH, Pereira DA. A framework to collect and extract publication lists of a given researcher from the web. International Journal of Web Engineering and Technology. 2017;12(3):234-52.
45. Ebadi A, Schiffauerova A, editors. A Computer System for Automatic Evaluation of Researchers' Performance. ISSI; 2015.
46. Ebadi A, Schiffauerova A. iSEER: an intelligent automatic computer system for scientific evaluation of researchers. Scientometrics. 2016;107(2):477-98.
47. ORCID. The ORBIT project 2018 [Available from: https://orcid.org/organizations/funders/orbit.
48. Publons. The power of Web of Science comes to Publons 2018 [Available from: https://publons.com/announcement/.
49. CASRAI. CRediT (Contributor Roles Taxonomy). 2019.
50. OpenRIF. CRO Taxonomy. 2019.
51. Paul PS, Kumar V, Choudhury P, Nandi S, editors. Temporal analysis of author ranking using citation-collaboration network. 2015 7th International Conference on Communication Systems and Networks (COMSNETS); 2015: IEEE.
52. Georgescu C, Wren JD. Algorithmic identification of discrepancies between published ratios and their reported confidence intervals and P-values. Bioinformatics. 2017;34(10):1758-66.
53. Grabitz P, Lazebnik Y, Nicholson J, Rife S. Science with no fiction: measuring the veracity of scientific reports by citation analysis. bioRxiv. 2017:172940.
54. Williams D, Dijoseph L, Corrigan J, Hsu E, Seger Y, Finstad S, et al. Relevance and focus shift: New metrics for the grant evaluation process pilot tested on nih grant applications (rip)2013. 1485-92 p.
55. Williams DE, Greenspan EJ, Corrigan JG, Lee JSH, Schnell JD, DiJoseph LG, et al. Piloting an approach to rapid and automated assessment of a new research initiative: Application to the National Cancer Institute's Provocative Questions initiative. Res Evaluat. 2013;22(5):272-84.
56. Request for Information (RFI). A software tool to assess the FAIRness of research outputs against a structured checklist of requirements [FAIRWare] 2019 [Available from: https://wellcome.ac.uk/what-we-do/our-work/open-research.
57. Chowdhury HA, Bhattacharyya DK. Plagiarism: Taxonomy, Tools and Detection Techniques. 2018.
58. Gipp B, Beel J. Citation based plagiarism detection: a new approach to identify plagiarized work language independently. Proceedings of the 21st ACM conference on Hypertext and hypermedia; Toronto, Ontario, Canada. 1810671: ACM; 2010. p. 273-4.
59. Acuna DE, Brookes PS, Kording KP. Bioscience-scale automated detection of figure element reuse. bioRxiv. 2018:269415.

60. Bucci EM. Automatic detection of image manipulations in the biomedical literature. Cell Death & Disease. 2018;9(3):400.
61. Droplets | ORI - The Office of Research Integrity 2019 [Available from: https://ori.hhs.gov/droplets.
62. Inc. IDI. Image Data Integrity 2019 [
63. Wang H, Ho L. The research and application of academic ethic and copyright of the reused figure for the publication based on NDLTD in Taiwan. ETD 2018 Taiwan: Beyond the Boundaries of Rims and Oceans: Globalizing Knowledge with ETDs; 26 Septemeber2018.
64. Nikitinsky N, Shashev S, Kachurina P, Bespalov A. Big Data and Machine Learning in Government Projects: Expert Evaluation Case. 2016.
65. Yu W, Yesupriya A, Wulf A, Qu J, Gwinn M, Khoury MJ. An automatic method to generate domain-specific investigator networks using PubMed abstracts. BMC medical informatics and decision making. 2007;7(1):17.
66. Liu O, Wang J, Ma J, Sun Y. An intelligent decision support approach for reviewer assignment in R&D project selection. Computers in Industry. 2016;76:1-10.
67. Karimzadehgan M, Zhai C. Constrained multi-aspect expertise matching for committee review assignment. Proceedings of the 18th ACM conference on Information and knowledge management; Hong Kong, China. 1646207: ACM; 2009. p. 1697-700.
68. Karimzadehgan M, Zhai C. Integer linear programming for Constrained Multi-Aspect Committee Review Assignment. Information Processing & Management. 2012;48(4):725-40.
69. Pupella V, Monteverde ME, Lombardo C, Belardelli F, Giacomini M. A semi-automatic web based tool for the selection of research projects reviewers. Studies in health technology and informatics. 2014;205:950-4.
70. Morgan AC, Way SF, Clauset A. Automatically assembling a full census of an academic field. PloS one. 2018;13(8):e0202223.
71. Global State of Peer Review: Publons; 2019 [Available from: https://publons.com/community/gspr.
72. Uzuner Ö, Luo Y, Szolovits P. Evaluating the State-of-the-Art in Automatic De-identification. J Am Med Inform Assn. 2007;14(5):550-63.
73. Neamatullah I, Douglass MM, Li-wei HL, Reisner A, Villarroel M, Long WJ, et al. Automated de-identification of free-text medical records. BMC medical informatics and decision making. 2008;8(1):32.
74. Meystre SM, Friedlin FJ, South BR, Shen S, Samore MH. Automatic de-identification of textual documents in the electronic health record: a review of recent research. BMC medical research methodology. 2010;10(1):70.
75. Ferrández Ó, South BR, Shen S, Friedlin FJ, Samore MH, Meystre SM, editors. Generalizability and comparison of automatic clinical text de-identification methods and resources. AMIA Annual Symposium Proceedings; 2012: American Medical Informatics Association.
76. Kushida CA, Nichols DA, Jadrnicek R, Miller R, Walsh JK, Griffin K. Strategies for de-identification and anonymization of electronic health record data for use in multicenter research studies. Medical care. 2012:S82-S101.
77. Liu Z, Tang B, Wang X, Chen Q. De-identification of clinical notes via recurrent neural network and conditional random field. Journal of biomedical informatics. 2017;75:S34-S42.
78. Superchi C, González JA, Solà I, Cobo E, Hren D, Boutron I. Tools used to assess the quality of peer review reports: a methodological systematic review. BMC Medical Research Methodology. 2019;19(1):48.

79. Thonon F, Boulkedid R, Delory T, Rousseau S, Saghatchian M, van Harten W, et al. Measuring the Outcome of Biomedical Research: A Systematic Literature Review. PloS one. 2015;10(4):e0122239.
80. Bornmann L. Measuring impact in research evaluations: a thorough discussion of methods for, effects of and problems with impact measurements. Higher Education. 2017;73(5):775-87.
81. Kulczycki E, Korzeń M, Korytkowski P. Toward an excellence-based research funding system: Evidence from Poland. J Informetr. 2017;11(1):282-98.
82.
83. Drive change in recognition and reward of academics 2019 [Available from: https://www.nwo.nl/en/news-and-events/news/2018/11/drive-change-in-recognition-and-reward-of-academics.html.
84. Kilicoglu H. Biomedical text mining for research rigor and integrity: tasks, challenges, directions. Briefings in Bioinformatics. 2017;19(6):1400-14.
85. Klampfl S, Kern R, editors. Machine learning techniques for automatically extracting contextual information from scientific publications. Semantic Web Evaluation Challenge; 2015: Springer.
86. Zschocke T. Enriching metadata in an international agroforestry research repository with funding-related information by mining grey literature. Procedia Computer Science. 2019;146:112-22.
87. Sirtes D, editor Funding acknowledgements for the German Research Foundation (DFG). The dirty data of the web of science database and how to clean it up. 14th international society of scientometrics and informetrics conference; 2013.
88. Zhang X, Zou J, Le DX, Thoma G. A semi-supervised learning method to classify grant support zone in web-based medical articles: SPIE; 2009.
89. Jonnalagadda S, Topham P, Gonzalez G, editors. Towards automatic extraction of social networks of organizations in PubMed abstracts. 2009 IEEE International Conference on Bioinformatics and Biomedicine Workshop; 2009 1-4 Nov. 2009.
90. Giles CL, Councill IG. Who gets acknowledged: Measuring scientific contributions through automatic acknowledgment indexing. Proceedings of the National Academy of Sciences of the United States of America. 2004;101(51):17599-604.
91. Jonnalagadda SR, Topham P. NEMO: Extraction and normalization of organization names from PubMed affiliations. Journal of biomedical discovery and collaboration. 2010;5:50-75.
92. Jongwoo K, Le DX, Thoma GR, editors. Automatic Extraction of Bibliographic Information from Biomedical Online Journal Articles Using a String Matching Algorithm. 19th IEEE Symposium on Computer-Based Medical Systems (CBMS'06); 2006 22-23 June 2006.
93. Drew CH, Pettibone KG, Finch FO, Giles D, Jordan P. Automated research impact assessment: a new bibliometrics approach. Scientometrics. 2016;106(3):987-1005.
94. Cook RB, Vannan SKS, McMurry BF, Wright DM, Wei Y, Boyer AG, et al. Implementation of data citations and persistent identifiers at the ORNL DAAC. Ecological Informatics. 2016;33:10-6.
95. Haak LL, Ferriss W, Wright K, Pollard ME, Barden K, Probus MA, et al. The electronic Scientific Portfolio Assistant: Integrating scientific knowledge databases to support program impact assessment. Science and Public Policy. 2012;39(4):464-75.
96. Kahng AB, Luo M, Nam G-J, Nath S, Pan DZ, Robins G. Toward Metrics of Design Automation Research Impact. Proceedings of the IEEE/ACM International Conference on Computer-Aided Design; Austin, TX, USA. 2840857: IEEE Press; 2015. p. 263-70.
97. Sváb-Zamazal O. Towards Automatic Classification of EU Projects for Supporting Open Fiscal Data Analysis. International Semantic Web Conference. 2019.

98. Terry RF, Allen L, Gardner CA, Guzman J, Moran M, Viergever RF. Mapping global health research investments, time for new thinking - A Babel Fish for research data. Health Research Policy and Systems. 2012;10(1):28.
99. Kim Y-M, Bellot P, Faath E, Dacos M, editors. Automatic annotation of bibliographical references in digital humanities books, articles and blogs. Proceedings of the 4th ACM workshop on Online books, complementary social media and crowdsourcing; 2011: ACM.
100. Kim Y-M, Bellot P, Faath E, Dacos M. Automatic annotation of incomplete and scattered bibliographical references in Digital Humanities papers. CORIA; 2012-03; Bordeaux, France2012.
101. Kenekayoro P, Buckley K, Thelwall M. Hyperlinks as inter-university collaboration indicators. Journal of Information Science. 2014;40(4):514-22.
102. Jensen LJ. One tagger, many uses-Illustrating the power of ontologies in dictionary-based named entity recognition. BioRxiv. 2016:067132.
103. McArthur D, Crompton H. Understanding public-access cyberlearning projects using text mining and topic analysis. J Am Soc Inf Sci Tec. 2012;63(11):2146-52.
104. Müller HM, Cachat J, Grethe JS, Marenco L, Martone ME, Ciccarese P, et al. A hybrid human and machine resource curation pipeline for the Neuroscience Information Framework. Database. 2012;2012.
105. Mugabushaka A-M, Papazoglou T. Information systems of research funding agencies in the "era of the Big Data". The case study of the Research Information System of the European Research Council. 2012.
106. Freyman CA, Byrnes JJ, Alexander J. Machine-learning-based classification of research grant award records. Res Evaluat. 2016;25(4):442-50.
107. Eito-Brun R. Knowledge dissemination patterns in the information retrieval industry: A case study for automatic classification techniques. World Patent Information. 2014;39:50-7.
108. Balsmeier B, Assaf M, Chesebro T, Fierro G, Johnson K, Johnson S, et al. Machine learning and natural language processing on the patent corpus: Data, tools, and new measures. Journal of Economics & Management Strategy. 2018;27(3):535-53.
109. Kayal S, Afzal Z, Tsatsaronis G, Katrenko S, Coupet P, Doornenbal M, et al., editors. Tagging Funding Agencies and Grants in Scientific Articles using Sequential Learning Models. BioNLP 2017; 2017 2017//: Association for Computational Linguistics.
110. Surkis A, Hogle JA, DiazGranados D, Hunt JD, Mazmanian PE, Connors E, et al. Classifying publications from the clinical and translational science award program along the translational research spectrum: a machine learning approach. Journal of Translational Medicine. 2016;14(1):235.
111. T KKA, Ko G, Walter. Applying Machine Learning to Compare Research Grant Programs. STI 2018 Conference Proceedings. 2018.
112. Haeffner-Cavaillon N, Graillot-Gak C. The use of bibliometric indicators to help peer-review assessment. Archivum Immunologiae et Therapiae Experimentalis. 2009;57(1):33.
113. Bai X, Zhang F, Hou J, Xia F, Tolba A, Elashkar E. Implicit Multi-Feature Learning for Dynamic Time Series Prediction of the Impact of Institutions. IEEE Access. 2017;5:16372-82.
114. Wright D, Williams E, Bryce C, le May A, Stein K, Milne R, et al. A novel approach to sharing all available information from funded health research: the NIHR Journals Library. Health research policy and systems. 2018;16(1):70.
115. Blandford D, Meyerson N, Droke D. Automating Grants Management and Review. SRA Journal. 1991;23(1):5-12.

116. Parreiras R, Kokshenev I, Carvalho M, Willer A, Dellezzopolles Jr C, Nacif Jr D, et al. A flexible multicriteria decision-making methodology to support the strategic management of Science, Technology and Innovation research funding programs. Eur J Oper Res. 2019;272(2):725-39.
117. Ardissono L, Petrone G, Segnan M, Torta G. Intelligent user interfaces for calendar management. Intelligenza Artificiale. 2014;8(2):115-27.
118. Wang J, Xu W, Ma J, Wang S. A vague set based decision support approach for evaluating research funding programs. Eur J Oper Res. 2013;230(3):656-65.
119. Fellner DW, Zens M. Electronic submission, managing and approval of grant proposals at the german research foundation based on standard internet and office tools. Journal of Universal Computer Science. 2000;6(3):356-66.

Appendix

Search Strategies

For preparation of the searches we conducted a Google Scholar search (allintitle: systematic review machine learning) to check the search strategies used in all systematic reviews on machine learning published in 2018, and we also expanded all endings of the root “fund*” in MEDLINE to include the keywords related to funders. We then constructed the following searches and conducted them on 2 November 2018.

Web of Science
TS=(grant OR grants OR "granting agency" OR "granting agencies" OR grantsmanship OR grantee OR grantees OR grantholders OR granter OR granters OR grantmaker OR grantmakers OR grantmaking OR grantmanship OR grantwrite OR grantwriters OR grantwriting OR funder OR funders OR fund OR funds OR "funding agency" OR "funding agencies")
TS=("machine learning" OR "learning based" OR automate OR automated OR automation OR automatic OR automating OR automatization OR automatize OR automatized)
#2 AND #1
Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-EXPANDED, IC Timespan=All yearsTS

Scopus
TITLE-ABS (grant OR grants OR "granting agency" OR "granting agencies" OR grantsmanship OR grantee OR grantees OR grantholders OR granter OR granters OR grantmaker OR grantmakers OR grantmaking OR grantmanship OR grantwrite OR grantwriters OR grantwriting OR funder OR funders OR fund OR funds OR "funding agency" OR "funding agencies") AND TITLE-ABS ("machine learning" OR "learning based" OR automate OR automated OR automation OR automatic OR automating OR automatization OR automatize OR automatized)

MEDLINE
(grant[Title/Abstract] OR grants[Title/Abstract] OR "granting agency"[Title/Abstract] OR "granting agencies"[Title/Abstract] OR grantsmanship[Title/Abstract] OR

grantee[Title/Abstract] OR grantee's[Title/Abstract] OR grantees[Title/Abstract] OR grantees'[Title/Abstract] OR grantholders[Title/Abstract] OR granter[Title/Abstract] OR granters[Title/Abstract] OR grantmaker[Title/Abstract] OR grantmakers[Title/Abstract] OR grantmakers'[Title/Abstract] OR grantmaking[Title/Abstract] OR grantmanship[Title/Abstract] OR grantwrite[Title/Abstract] OR grantwriters[Title/Abstract] OR grantwriting[Title/Abstract] OR funder[Title/Abstract] OR funders[Title/Abstract] OR fund[Title/Abstract] OR funds[Title/Abstract] OR "funding agency"[Title/Abstract] OR "funding agencies"[Title/Abstract] OR "Financing, Organized"[Mesh]) AND ("machine learning"[Title/Abstract] OR "learning based"[Title/Abstract] OR automate[Title/Abstract] OR automated[Title/Abstract] OR automation[Title/Abstract] OR automatic[Title/Abstract] OR automating[Title/Abstract] OR automatization[Title/Abstract] OR automatize[Title/Abstract] OR automatized[Title/Abstract] OR "Machine Learning"[Mesh])

DBLP *(Note: Phrase search was disabled due to internal error during the search)*
(grant$|grants$|granting$|grantsmanship$|grantee$|grantees$|grantholders$|granter$|granters$|grantmaker$|grantmakers$|grantmaking$|grantmanship$|grantwrite$|grantwriters$|grantwriting$|funder$|funders$|fund$|funds$|funding$)
(machine$|learning$|based$|automate$|automated$|automation$|automatic$|automating$|automatization$|automatize$|automatized$)

Google Scholar:
allintitle: grant machine learning
allintitle: fund machine learning
allintitle: grant learning based
allintitle: fund learning based
allintitle: grant automate
allintitle: fund automate

Detailed Funder Workflow

1 Secure funding

1.1. Obtain funds (or receive funds from government for a call)
1.2. Define or refine a topic for research
1.2.1. Conduct knowledge synthesis ("horizon scanning")

2 Develop a grant call

2.1. Hold an expert consultation / invitational conference
2.2. Assess stakeholder involvement (i.e. citizens and patients)
2.3. Assess diversity questions (race, sex, culture)
2.4. Assess potential real-world implementation
2.5. Decide who can apply (e.g. define eligibility criteria, individual vs multi-consortia type of applications, partners, NGO, and patient involvement)
2.6. Decide how much money can an applicant apply for and how much they need to partake in costs
2.7. Decide grant assessment criteria (e.g. quality and relevance criteria)
2.8. Decide time points for grant application/review/start of funding
2.9. Decide on number of application rounds (e.g. first short, then detailed proposals)
2.10. Decide review procedure characteristics (e.g. approval committee or external peer reviewer, blind or open reviews, on-site or off-site reviewing, rebuttal or no rebuttal phase)
2.11. Decide if interviews with applicants will follow grant review procedure and define the type of the interviews
2.12. Write reviewer or interview instructions/assessment criteria
2.13. Write a grant call

3 Disseminate the grant call

3.1. Determine grant communication strategy (e.g. posting on funder website, distribution through email and social media, replying to applicant inquiries)
3.2. Disseminate the grant call
3.3. Decide on (and conduct) workshops for applicants
3.4. Decide on sharing answers of received applicant inquiries (e.g. publish FAQ)

4 Obtain proposals

4.1. Use a proposal submission system
4.2. Authenticate applicants' ID and biographical information
4.3. Check applicants' track record (e.g. publications, citations, previous funding, management skills, open science badges)
4.4. Checking applicants' potential conflicts of interest
4.5. Check applicant's team completeness and letters of commitment authenticity
4.6. Check applicants' submitted checklists (e.g. ethics assessment or grant call checklists)
4.7. Authenticate applicants' institutions approvals
4.8. Authenticate applicants' ethics approvals
4.9. Conduct plagiarism check
4.10. Conduct image manipulation/duplication check
4.11. Check titles and abstracts adherence to call or reporting guidelines
4.12. Check project introduction (background) section
4.12.1. Compare or check if the introduction referred or conducted (automated) systematic reviews on the proposal's topic
4.13. Check the proposal's study type and adherence to reporting (protocol) guidelines
4.14. Check the choice of outcomes and outcome measurement tools
4.15. Check for (non)reported limitations
4.16. Check for projects risk assessment and contingency plans
4.17. Check for real-world (societal) impact prediction
4.18. Conduct proposals ethics assessment
4.19. Check for budget (expenditure) feasibility and credibility
4.20. Check proposal's timeline credibility (e.g. Gantt chart feasibility)
4.21. Check for overall proposal feasibility

5 Find reviewers

5.1. Locate reviewers (invite known or new reviewers)
5.2. Authenticate reviewers ID and expertise
5.3. Check for reviewers' potential conflicts of interests
5.4. Send proposals to reviewers

6 Obtain reviews

6.1. Collect review reports (use submission system)
6.2. Check review quality and criteria adherence
6.3. Summarize review reports (draft or automate consensus report, conduct meetings with reviewers)
6.4. Send reviews to applicants
6.5. Receive and check applicants' rebuttals
6.6. Re-score proposals after rebuttal phase
6.7. Make a final list of accepted proposals

7 Distribute the funds

7.1. Negotiate and sign the contract with applicants
7.2. Transfer funds to the applicants

8 Monitor the grants

8.1. Check study process, progress reports, milestone and deliverable completion
8.2. Check (open) access for publications and adherence to FAIR principles for data
8.3. Check funding expenditure

9 Grant and portfolio evaluation

9.1. Goal and financial evaluation

9.2. User analysis (e.g. local, national, international, and cross-sector stakeholder and public engagement)
9.3. Scientific impact analysis (e.g., citations and altmetrics of publications and registered patents)
9.4. Knowledge impact analysis (e.g. change of practice, knowledge synthesis changes)
9.5. Return on Investment (ROI) of funded projects

10 Stakeholder engagement and human resource management*

10.1. Media and web content generation
10.2. Internal report generation
10.3 Managing personnel, resources and services

*Steps belonging to this category have not been further expanded upon as the focus of the project was on the grant process rather than inner working of an organization.