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## Technology-Assisted Literature Reviews with Technology of Artificial Intelligence: Ethical and Credibility Challenges

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### Abstract

General discussion around artificial intelligence (AI) seems to be mostly concerned about potential benefits or hazards. While AI excels in automating basic and simple repetitive tasks, this is not a synonym for creativity, nor ethically sustainable unless the role is simple. Machine learning, deep learning and AI are trendy phenomena. However, the ethicality and credibility of the usage of AI in Technology-assisted literature reviews are raising questions. A systematic literature review was conducted to the SCOPUS database and Google Search. The PRISMA framework was used for the literature review. It was explored how AI is used to conduct -or assist in literature reviews. The results indicate that different scientific fields discuss issues relating to biases in AI technology and there is no consensus about what keywords and definitions should be to describe the same issue. AI has its place in the methodology of literature reviews, and this methodology continues to develop, but there are unsolved issues that how to create a tool with minimal bias and understand the current limitations of the technology of artificial intelligence. The empirical observation is that there are no specified keywords for the articles which relate to artificial intelligence-assisted literature reviews, which creates limitations for the generalisability of the results of this systematic literature review. Thus, this study has made several basic discoveries during this systematic literature review and their results are discussed. AI still poses bias risk and AI assisted literature reviews cannot be reliable without human supervision and there is no consensus on how AI assisted literature reviews should be classified in keywords and titles. It remains an open question whether there are any more hidden qualitative hypotheses in the development of reliability and validity of AI technology, which are waiting for discovery.

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## 1. Introduction

In the field of contemporary scientific research, a well founded question can be presented: how artificial intelligence assisted literature reviews affect the way how literature reviews are done? It seems that unforeseen issues emerge from this technology and scientific community should discover limitations of this new technology. This study will be qualitative research, not statistical research. Therefore, in this study preliminary qualitative hypotheses on artificial intelligence in technology-assisted literature reviews will be presented, which includes how artificial intelligence in the literature review process had been researched. In addition, there will be a few research questions. A few working qualitative hypotheses have been developed during research design discussion of this study. It was done by reflecting cumulated knowledge in this field to create the working qualitative hypotheses.

There is other scientific research, which have uses qualitative hypotheses [1], [2], [3] to make qualitative research [1]. The working qualitative hypotheses are developed to support clarifying analysis of the research questions [4]. Chigbu (2019) has created three criteria for qualitative research hypotheses formulation, which are: “*In qualitative research, it is common to investigate research hypotheses that can be viewed in three possible ways: Attributive (meant to describe a scenario, situation or event), associative (meant to predict an outcome) and causal (meant to create an understanding of relationships)*” [4]. Working qualitative hypotheses was created to understand attributes of the scenario of artificial intelligence, to predict outcome and understanding working hypothetical background assumptions what literature review offers answer to the artificial intelligence. The qualitative hypotheses can be created during the research or before it [5].

The first qualitative hypothesis is that artificial intelligence technology-assisted literature reviews are published in top-tier journals (JUFO 3). The second qualitative hypothesis is that artificial intelligence is used doing part of the literature review and it does not fully replace humans. The third qualitative hypothesis is that artificial intelligence limitations are mentioned in the literature review and ethical issues relating to bias of steering data. The fourth qualitative hypothesis is that artificial intelligence has solved issues relating to misinterpretation of what humans do in literature reviews. In addition, a few research questions relating to ethics and misestimation of the performance of artificial intelligence have been created. Therefore, main research questions are: (RQ1) What ethical issues relate to the usage of artificial intelligence on technology-assisted literature reviews? (RQ2) What are the actual performances of artificial intelligence on technology-assisted literature reviews?

## 2. Literature review

A literature review can be theoretical by its nature [6], it can even be a review of empirical data sets of previous studies because the empirical methodology is about data which reflects reality which can be measured [7], [8, p. 16]. To make the literature review credible there must be a typology which is used to do the literature review [6] and use structured approach in collecting data from literature review datasets [9]. Many scholars in the information system science field agree that literature reviews should be methodologically rigorous [10]. Therefore, there is a debate related to the question of what a sound process is methodologically to conduct reliable and valid systematic literature reviews.

Currently, artificial intelligence (AI) can be called with different definitions such as machine learning (ML) and deep learning (DL), and artificial intelligence is a trendy topic [11], and this phenomenon has spread around the professional and academic world, and it is supposed, that these technologies will continue to change the world. Thus, the research area has saturated the amount of private corporate research and AI research has been declining in the 2000 century and natural language processing research has been on the decline [12, p. 54-55]. These phenomena can be called by a definition, which is an AI winter [12, p. 54], [13]. The AI winter is a phenomenon where the research field of AI is becoming a trendy topic and it received a large amount of funding thus the results are not that significant and expectations for output are not met [13], [14, p. 8]. Thus, it is a myth that this would mean the end of the development of AI [13]. The development of AI can be seen centuries later [15]. There is a political race between the so-called power structures of the U.S. and China. Both nations compete to determine which one of them can develop

AI firstly to be more advanced [16]. However, there is nothing new in the historical sense that failures in the development of technology are rationalized as single isolated cases [17]. Beliefs of development are dusted off in late times, when new experiments in AI are tried again when new technological development occurs [18]. This vision of significant development in AI has the possibility to create phenomena of a third AI winter [14], [19] where pessimistic beliefs are again discovered, because it is difficult to say what is the time when the development of the technology is suitable [20]. Expectations for the performance of AI can be overestimated by the public, even if it has in fact limited area where it is effective [18] and this AI winter actualises when funder expectations are not met with the output when research is expanded, and results are not as useful [21].

In addition, AI study needs evaluation of ethical issues when AI is used to create text, create images, search for information, analysis content of texts and the technology does not have transparency, because of its proprietary software license conditions. There is research that output of AI will shape each human’s reality [22]. Hence, giving AI same credibility and trustworthiness being a scientific tool has issues, which must be addressed. There are concerns about how AI will shape each human’s way of thinking and process information. In 1997 there was concern that enough attention had been not used to look-ahead reasoning of AI [23]. In 2023-year, a study shows that AI did in fact affect humans that there was a loss of decision-making of humans that it makes humans lazy and that there are impacts to security and privacy [24]. The results can be described as concerning: “*The findings show that 68.9% of laziness in humans, 68.6% in personal privacy and security issues, and 27.7% in the loss of decision-making are due to the impact of artificial intelligence in Pakistani and Chinese society.*” [24] There is research which show that bias, which is inserted to AI, will influence people to adapt biased knowledge, who are exposed to the AI output [22], [25]. Also, the AI poses a new emerging cybercrime threat to society, because it is being used to commit cybercrimes [26].

### 3. Research design

A Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) literature review quality system had been used to answer research the qualitative hypotheses and the research questions. The PRISMA methodology have been used for example in medicine to make systematic or meta-analyses of previous research [27], [28], [29]. The literature review can be done with qualitative research approach [30] and this study is qualitative, not statistical study. The research data will be analysed with qualitative research methodology, which is a critical interpretive synthesis [31]. The critical interpretive synthesis is used to develop concepts and theory [31]. There is no total consensus [31], how interpretive research methodology research hierarchy should be conducted [32]. Research data is collected from the SCOPUS database and from Google search. Please see Figure 1 for an illustration of the data processing.

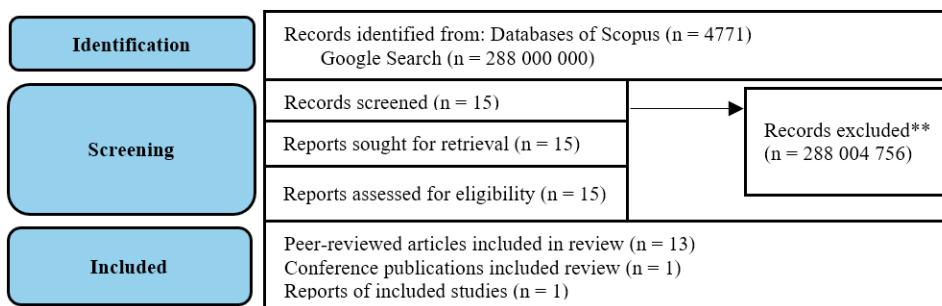


Fig. 1. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) a flow chart how systematic literature review was conducted.

#### 3.1. Data sampling

Data sampling was done by selecting research which relates to how AI is used to make literature reviews in science and how AI technology-assisted literature reviews have been published. Selected publications were processed by

documents discursive approach [33, p. 7]. The critical interpretive synthesis a review methodology allows researchers to identify previous research underlying assumptions and designs of previous studies and informed data integration [34], [35]. The critical interpretive synthesis allows usage of both qualitative and quantitative methodology [36]. The SCOPUS database was reviewed, which gave us 4771 documents as results on 6.3.2024 and Google Search did give 288,000,000 hits. Search parameters were in the SCOPUS: Article title, abstract, keywords: "literature review" AND "machine learning" and in Google Search: "machine learning-assisted literature review". This makes a total of 288 004771 hits. Google Search was used to expand the literature review search, to cover the grey literature and to select relevant documents for screening. It was decided to compare the keywords of the articles and the content of the articles to make an exclusion, which articles will be downloaded. There was no correlation between keywords, titles and abstract content when randomly selecting articles from search results. It was decided to make use custom search parameters, which led to the selection of 15 documents for further analysis.

### 3.2. Data coding and analysis

The data was sampled by creating a table, which included title of document, search parameters and keywords. Please see Table 1 for the search parameters and title names of publications are in Table 2 with an identification number\*\*.

Table 1. Search parameters on SCOPUS and Google Search parameters.

**	Search parameters on SCOPUS	keywords
1	( KEY ( "statistics & research methods" OR "Technology-assisted review" OR "systematic review" OR "Artificial intelligence" OR "machine learning" ) AND TITLE ( "Artificial intelligence" OR "Machine learning" ) AND TITLE ( "in" OR "assisted" OR "assist" OR "using" OR "with" ) AND TITLE ( "literature review" OR "literature reviews" ) AND ABS ( "ASReview" OR "PRISMA" AND ( "systematic reviews" OR "Machine Learning assisted systematic reviewing" OR "assist the performance of systematic reviews" OR "Machine Learning Methods for Systematic Reviews" OR "Based on Machine Learning" OR "Role of Artificial Intelligence" OR "machine learning framework" OR "An Assisted Literature Review using Machine Learning" OR " A systematic literature review" ) ) )	Active learning; Machine learning; Systematic review; Technology-assisted review
2	( KEY ( "statistics & research methods" OR "Technology-assisted review" OR "systematic review" OR "Artificial intelligence" OR "machine learning" ) AND TITLE ( "machine learning-assisted" OR "Artificial intelligence in systematic reviews" OR "studies using machine learning techniques" OR "based on artificial intelligence" OR "Based on Machine Learning" ) AND ABS ( "PRISMA" OR "ASReview" OR "systematic literature review" OR "systematic review" OR "systematic reviews" OR "NLP" ) )	component; formatting; insert; style; styling
3	( KEY ( "assisted literature review" OR "statistics & research methods" OR "automating literature review" ) AND TITLE ( "Machine Learning assisted systematic reviewing" OR "assist the performance of systematic reviews" OR "Machine Learning Methods for Systematic Reviews" OR "Based on Machine Learning" OR "Role of Artificial Intelligence" OR "machine learning framework" OR "An Assisted Literature Review using Machine Learning" ) OR ABS ( "Machine learning assisted systematic reviewing" OR "automated reviews" OR ml ) )	Artificial intelligence; Machine learning; Meta-analysis; Screening; Systematic reviews
4	( KEY ( "assisted literature review" OR "statistics & research methods" OR "automating literature review" ) AND TITLE ( "Machine Learning assisted systematic reviewing" OR "assist the performance of systematic reviews" OR "Machine Learning Methods for Systematic Reviews" OR "Based on Machine Learning" OR "Role of Artificial Intelligence" OR "machine learning framework" OR "An Assisted Literature Review using Machine Learning" ) OR ABS ( "Machine learning assisted systematic reviewing" OR "automated reviews" OR ml ) )	automating literature review; machine learning; natural language processing
5	TITLE-ABS-KEY ( "statistics & research methods" AND "Artificial intelligence" AND "in" AND "systematic reviews" OR "systematic review" )	epidemiology; preventive medicine; statistics & research methods
6	TITLE-ABS-KEY ( "machine learning-assisted systematic literature reviews" )	information technology; statistics & research methods; systematic review
7	TITLE-ABS-KEY ( "statistics & research methods" AND "Artificial intelligence" AND "in" AND "systematic reviews" OR "systematic review" )	Applied case study; Machine learning; Machine learning configurations; Natural language processing; Systematic review screening; Transfer learning
8	TITLE-ABS-KEY ( "statistics & research methods" AND "Artificial intelligence" AND "in" AND "systematic reviews" OR "systematic review" )	epidemiology; general medicine (see internal medicine); statistics & research methods
9	TITLE-ABS-KEY ( "statistics & research methods" AND "Artificial intelligence" AND "in" AND "systematic reviews" OR "systematic review" )	clinical trials; health informatics; statistics & research methods
10	Google Search	Keywords
11	machine	Artificial intelligence; ASReview; Machine learning; Screening; Systematic review
12	learning-assisted literature	assisted literature review; literature review; machine learning; semantic topic detection; text and data mining
13	review	Systematic reviews; Mapping review; Evidence-based practice; software development; Machine learning, Automatization
14		Learning algorithms; Machine learning; Open source software; Open systems
15		text attribution; Automated system-cognitive analysis; Eidos intelligent system

From the Table 1 it can be empirically discovered that keywords, titles of documents and search parameters do not correlate with each other. It takes multiple tries to find intuitively correct search parameters to locate documents which relate to using AI for assisted literature reviews or using AI to conduct literature reviews. After multiple tries a total of 15 documents are identified, which relate to the research qualitative hypothesis and research questions, with custom search parameters. Those 15 documents were collected from Google Search and the SCOPUS database. Please, see Table 2 for the documents.

Table 2. Identified articles for analysis.

**	Title of document	JUFO ranking (empty, 0, 1,2,3)*	Type
1	Systematic review using a spiral approach with machine learning	1* [37]	Peer-reviewed article
2	Research Methods and Progress of Text Sentiment Analysis Based on Machine Learning	[38]	Conference article
3	The efficiency of machine learning-assisted platform for article screening in systematic reviews in orthopaedics	1* [39]	Peer-reviewed article
4	System for Semi-Automated Literature Review Based on Machine Learning	1* [40]	Peer-reviewed article
5	Protocol for a systematic review on the methodological and reporting quality of prediction model studies using machine learning techniques	1* [41]	Peer-reviewed article
6	Artificial intelligence in systematic reviews: promising when appropriately used	1* [42]	Peer-reviewed article
7	Iterative guided machine learning-assisted systematic literature reviews: a diabetes case study	1* [43]	Peer-reviewed article
8	Protocol for development of a reporting guideline (TRIPOD-AI) and risk of bias tool (PROBAST-AI) for diagnostic and prognostic prediction model studies based on artificial intelligence	1* [44]	Peer-reviewed article
9	Quality of reporting of randomized controlled trials of artificial intelligence in healthcare: a systematic review	1* [45]	Peer-reviewed article
10	Machine Learning Methods for Systematic Reviews: A Rapid Scoping Review	[46]	Peer-reviewed article
11	Machine Learning assisted systematic reviewing in orthopaedics	1* [47]	Peer-reviewed article
12	An Assisted Literature Review using Machine Learning Models to Identify and Build a Literature Corpus	[48]	Peer-reviewed article
13	Machine learning computational tools to assist the performance of systematic reviews: A mapping review	1* [49]	Peer-reviewed article
14	An open source machine learning framework for efficient and transparent systematic reviews	2* [50]	Peer-reviewed article
15	INTELLECTUAL ATTRIBUTION of LITERARY TEXTS (finding the dates of the text, determining authorship and genre on the example of Russian literature of the XIX and XX centuries)	[51]	Non-peer-reviewed publication (a report)

### 3.3. Limitations

The Table 1 show the challenge that there are no rigorous search parameters to locate all studies relating to AI assisted literature review methodology. It made this study experimental and created limitations for generalization of the discoveries. In addition, the qualitative analysis gives limitation that what prior knowledge researcher has and how during research the understanding of the objects chance affect how much a new knowledge can be obtained during the research process.

## 4. Analysis and findings

The PRISMA methodology is allows the use of embodiments [37]. AI tools are promising for assisting in systematic reviews, when the algorithms are used appropriately, and methodological soundness of the algorithms is assured [42]. For systematic reviews, ML tools are the most investigated method to assist systematic reviews, and the development of ML algorithms are in the hand of working groups [49]. The sentiment dictionary analysis requests a large amount of manual annotation, and it is nowadays not commonly used [38]. The Eidos intellectual system can successfully discover dates of texts, detect genres of the text, and detect authorship of the texts, when certain mathematical models, numerical calculation and screening forms of processing are used in the Eidos [51]. ML is significantly better at assisting literature reviews than previous methodologies, but efficiency will decrease when the complexity of research questions increases during the research process of the literature review [39]. However, without an optimal steering dataset for ML it will be a challenge to make replicable results [37] and this will affect credibility

of the literature review. The combined ML models seem to have enough sensitivity and accuracy for the automated literature review, when multiple unweighted ML models are used [40]. Bias in ML can be overcome by training datasets which is coded with the help of humans and humans oversee the learning of the ML algorithm [43], [46]. ML is effective in retrieving relevant studies in orthopaedics [47]. There are demonstrations that using active ML will have far more efficient review performance than manually reviewing datasets of systematic reviews [50].

Still, there are a limited number of studies which report their systematic reviews of methodological quality in ML based prediction models and these models have a risk for bias [41]. Even in random control trial studies the AI intervention was insufficiently reported [45]. There is a need to make models for assisted literature review, which detect relevant documents in the review process [48]. ML techniques lack good classification and prediction of context semantics and DL is proposed as the next solution to make better learning of the data [38]. Thus, ML methodologies have a risk for biases. One study says that there is no guideline for medical clinicians to detect bias from AI tools in practice [44]. These results from the literature show that there is an existential problem. The answer to the first qualitative hypothesis is that the research did not discover many publications in top-tier journal articles relating to the usage of AI technology-assisted literature reviews or using AI to fully conduct literature reviews from beginning to end without human assistance. Top-tier journals are ranked JUFO three and only one JUFO two ranking article was discovered. To answer the second qualitative hypothesis, it seems that AI has not replaced humans in the literature review process, and it is used as an assisted tool in literature reviews.

The answer third qualitative hypothesis is that the limitations of AI are mentioned in some articles relating to biases of datasets and need assistance of humans to make valid training datasets. The answer fourth qualitative hypothesis is that AI has not solved the misinterpretation of results, because of biased datasets or limitations of data analysis of AI. The answer to first research question (RQ1) is that there are ethical issues which arise from previous studies relating biases of datasets. The ethical issues are bias in dataset, which gives output which that causes unethical choices for example in selection treatment or making decisions. Also, limitations of the supervised data need human assistance so that technology does not make incorrect choices or predictions, which are believed to be true. The answer to second research question (RQ2) is that there are limitations of technology to make performance on output, because more complex research designs demand parameters, which decrease the effectiveness of AI and there is still a need for human assistance to do literature reviews. In some cases, AI assisted literature reviews are time-efficient and accurate retrieving relevant studies when parameters can be controlled, for example in the scientific field of orthopaedics.

## 5. Discussion and conclusion

Table 1-2 and process of the literature review shows that detection of relevant publications with search parameters is not obvious, because there are different keywords, titles and search parameters to discover same research subject to AI assisted literature reviews and no consensus how keywords and titles should be used is missing to label research. The one of basic discovery is that there was no exact keywords and search parameters to identify articles relating to AI technology-assisted literature reviews. The keywords of the publications are not equivalent and there are different keywords used in field of medicine (for example: statistics & research methods) to describe AI assisted literature reviews than in other scientific fields. A recent publication from this year (2024) indicates that there is no established consensus on keywords (see example [52]). Thus, consensus is problematic criterion for knowledge, because history of science show that it does not guarantee that research have made the absolute basic discovery of knowledge, which would be the final word in science [53, p. 51-52]. Even mathematics is a language [54], which describes abstract things, and mathematics is more like philosophy [55], and this study show clearly the same object, or phenomenon can be described and defined with different language concepts for example different keywords discuss with the same research object. Still, it is vital to make a distinction between what is described and how it is described [54]. This study is not capable give the final word for usage of keywords.

The use of AI has been expanded and it is portrayed as a promising problem solver in many areas [56]. Thus, discussion of bias in supervising dataset [22], [57], [58] and limitations of the technology creates an existential crisis, when AI should be used without critical thinking as a tool for decisions or a method to solve issues. It has been said that AI has potential when it is used appropriately [42]. When scientific literature review making will be transferred to AI or at least be assisted by AI, it will have impacts. It can be said that humans make errors [59], what will happen when AI do it? By considering the cognitive capacity of a human being, and think about the learning process that is

usually time-consuming, how can researchers speed it up safely? Or is this something that from a psychological viewpoint every researcher should not even consider? Without transparency and critically assessing all part of the research process, the AI creates outputs which are biased [22], [63], [64], [58], [25], [52], [57], [60], [61] and therefore, it will not solve the human error issue and we must avoid creating a norm to believe that the technology gives us always credible information, even though there are reliability, validity and bias issues with technology of AI. It can be proposed that discussion will expand to the following directions: what are hidden qualitative hypotheses in the development of technology, how much AI can be developed before absolute limitations are reached, and how human and machine symbioses will develop? At this time, it seems to be too good to be true that the AI can defeat totally bias or totally error of judgment in decision making and predictions. The AI winter can occur again when expectations for hypothetical development of technology does not fit with reality of actual results.

### *5.1. The Importance of putting your mind into work*

If literature review is considered a phase in research, where learning process on the topic of the study takes place and an individual researcher outsources him/herself from the process, what remains? Isn't this learning process central for any scientific study, where any researcher must learn the ins and outs of studied phenomena or research objects? If scientific process moves the information search and evaluation task to a digital assistant that is AI-based, it is an artefact that has been put together by someone or something and then trained to be able to perform assigned tasks. The underlying problem here is that design choices are made by developers and shortcomings in training data are then transmitted further in the form of different biases and limitations to those using these systems. The same applies to ethical and moral questions which are further transmitted to those using the AI system, and in the worst case in form of black box. Martinson (1974) has warned us to avoid methodological narcissism [62], when a researcher starts to believe to one methodology, it causes that research is not developing new knowledge.

*“Bias is typical challenge in process of a qualitative study, for instance during the analysis of data, if there is for instance only one researcher, who is coding a data”* [65] *“Algorithms often fail to perform as expected due to various data, model, and market biases. Algorithmic bias management capability consists of three primary dimensions, namely data, model, and deployment capabilities.”* [66] Pre-understanding remains to be unsolved issue, which is present on every human's current reality [67]. Many researchers probably use their previous studies as foundations for new research [67] and enriching old research is limited [67]. Are there anything new that knowledge advances only through critical thinking and rejection of an old “scientific belief” [53, p. 29-30, p. 78-79]. It seems that we do not have a methodology, which always gives the newest knowledge and there are no deficiencies. Currently, technology of AI does not currently eliminate issues in interpretation. That is because results will be exposed to humans. Interpretation issues are real, because there is credible evidence that different researchers understand the same abstract subject or – object differently and make different interpretations from the same research data [72], [73]. Thus, it remains an unsolved issue what are the actual limits of the technology in logical continuity and when all hidden qualitative hypotheses are discovered, and no new inventions are no longer possible to discover as new knowledge. The error itself is a social construct, because humans decide that what an event will be classified as an error. The universe allows many events to occur, even humans do not want them to occur, or they see it as an error

### *5.2. Standard quality or novel innovations?*

While top-tier journals do their best to maintain the level and quality of the publication as high standard as possible, this leads to a paradox which this study refer to as "standard quality over risky Innovations". Based on the conducted systematic literature review, it seems that top-tier journals seldom publish interesting and innovative articles that are not so polished to the research community from new research frontiers. This refers to the practice, where rigor and tradition outdoes creativity and innovation. However, now it seems that novel and creative articles are not automatically submitted or published in these top-tier journals. While it is true that the faster research is published, the better [68] - it is still problematic [69], when research is taking place in new frontiers, and thus it is considered a new kid on the block [70]. There are underlying issues in science, which are caused by this phenomenon of staged competition [71, p. 50-51]. The role of AI in research is evolving, and while it provides many benefits, thus there are ethical discussions. If Laissez-faire approach is being embraced, in the worst-case it might face the risk of academic

AI winter. Currently, results show that an absolute autonomous AI is not possible, because humans are needed to steer AI, DL and ML tools [43], [46] and guidelines are needed to detect bias [44].

### 5.3. Future work?

First, future scientific research should conduct more specific research related to biases related to AI-assisted literature review and how to cope with the biases. Second, future scientific research should study how to make AI-assisted literature review as transparent as possible to ensure that research is scientific and not based on “black box technology”. Thirdly, future scientific research should study how to combine human intelligence as effectively as possible with digital tools of artificial intelligence (AI, DL, ML) and at the same time take care of the best possible interpretation and understanding of a research subject. Fourthly, future scientific research should do more basic research that what hidden qualitative hypotheses are available on the development of technology relating to the synthesis of discrete data to gain more precise and reliable results with that technology. After qualitative research a quantitative hypothesis can be established, because researchers pre-understanding and pre-theories are progressed. Fifthly, a theory should be created to explain why and when development of AI technology or technology in general is possible.

### 5.4. Practical recommendations for future AI assisted literature reviews

Currently, there is no such thing as an absolute autonomous AI, which does not need human supervision that decision and analyses which AI makes, because datasets can be biased or when AI usage is expanded by ignoring the limitations of models then AI technology start producing results which are invalid. To make AI assisted literature review that AI supervision datasets should be ascertained that there are minimal amount of bias and the limitations of models in AI should be made transparent, because otherwise we create logical continuity where biased or/and misinformation transform facts which are accepted without critical thinking. There is no credible evidence that some literature reviews process could be transferred to AI without human supervision, because there is still risk for wrong predictions or wrong decisions without human supervision AI tools transparency how the technically the module works is essential, when reliability and validity of the results are being assessed. Scientific community should support open-source tools, where source codes can be assessed without black box -dilemma.

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