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Artificial Intelligence and COVID-19: A Systematic umbrella review and roads ahead

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A R T I C L E I N F O

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A B S T R A C T

Artificial Intelligence (AI) has played a substantial role in the response to the challenges posed by the current pandemic. The growing interest in using AI to handle Covid-19 issues has accelerated the pace of AI research and resulted in an exponential increase in articles and review studies within a very short period of time. Hence, it is becoming challenging to explore the large corpus of academic publications dedicated to the global health crisis. Even with the presence of systematic review studies, given their number and diversity, identifying trends and research avenues beyond the pandemic should be an arduous task. We conclude therefore that after the one-year mark of the declaration of Covid-19 as a pandemic, the accumulated scientific contribution lacks two fundamental aspects: Knowledge synthesis and Future projections.

In contribution to fill this void, this paper is a (i) synthesis study and (ii) foresight exercise. The synthesis study aims to provide the scholars a consolidation of findings and a knowledge synthesis through a systematic review of the reviews (umbrella review) studying AI applications against Covid-19. Following the PRISMA guidelines, we systematically searched PubMed, Scopus, and other preprint sources from 1st December 2019 to 1st June 2021 for eligible reviews. The literature search and screening process resulted in 45 included reviews. Our findings reveal patterns, relationships, and trends in the AI research community response to the pandemic. We found that in the space of few months, the research objectives of the literature have developed rapidly from identifying potential AI applications to evaluating current uses of intelligent systems. Only few reviews have adopted the *meta*-analysis as a study design. Moreover, a clear dominance of the medical theme and the DNN methods has been observed in the reported AI applications.

Based on its constructive systematic umbrella review, this work conducts a foresight exercise that tries to envision the post-Covid-19 research landscape of the AI field. We see seven key themes of research that may be an outcome of the present crisis and which advocate a more sustainable and responsible form of intelligent systems. We set accordingly a post-pandemic research agenda articulated around these seven drivers.

The results of this study can be useful for the AI research community to obtain a holistic view of the current literature and to help prioritize research needs as we are heading toward the new normal.

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Contents

1. Introduction . . . 5899
2. Umbrella review: Review of reviews on ai applications against COVID-19 . . . 5900
   2.1. Materials and methods . . . 5900
      2.1.1. Study planning . . . 5900
      2.1.2. Data analysis . . . 5901
   2.2. Findings . . . 5901
      2.2.1. Bibliometric analysis . . . 5901
3. Quo vadis artificial intelligence? Ai in post-covid-19 era . . . 5912
   3.1. Data efficient models . . . 5912
   3.2. Sustainable models . . . 5913
   3.3. AI democratization . . . 5914
   3.4. Autonomous everything . . . 5914
   3.5. Generative everything . . . 5915
   3.6. Ethical AI . . . 5915
   3.7. Precision AI . . . 5916
4. Limitations and future scope . . . 5916
   4.1. Limitations . . . 5916
   4.2. Future scope . . . 5917
5. Conclusion . . . 5917
   Declaration of Competing Interest . . . 5917
   Appendix. Included reviews . . . 5917
   References . . . 5919

1. Introduction

Few weeks after its outbreak in December 2019, the coronavirus disease (Covid-19) was declared as a pandemic by the World Health Organization (WHO) on March 11, 2020[1]. Roughly a year into the crisis, it is high time to take a synthetic view of the current situation, and to start accordingly preparing the beyond crisis. Covid-19 is not the first or the only punctuation in modern times, but it is the first punctuated event where Artificial Intelligence (AI) and associated technologies are in wide use (Haleem et al., 2020a; Javaid et al., 2020a; Javaid and Haleem, 2019). Being a powerful tool, AI has joined the fight against Covid-19 and actively contributed to contain the global health crisis (Naudé, 2020a; Vaishya et al., 2020). As a result, the impacts and the needs posed by Covid-19 have largely accelerated, at scale and pace, the growth and adoption of AI-based solutions. It is becoming clear now that the way AI is currently used will have a profound impact on the way AI will be viewed and used going forward. This review advocates the need of synthesizing the one year of AI literature dedicated to Covid-19, as well as the importance of shaping the future of this technology beyond the current pandemic. Studies in this vein are required, at this time, if we are to keep in step with AI changing realities and paradigm shifts prompted by the pandemic. Accordingly, this review has a twofold objective:

First, it proposes a panoramic view of where AI is positioning in the arsenal to fight Covid-19. A thorough investigation of the bulk of AI literature addressing Covid-19 issues identified a large number of existing literature review studies. Indeed, in the last year, there has been much interest from both the scientific and industrial communities in exploring the potential of AI to support the response to the pandemic across a wide range of clinical, societal, and economical challenges. The expanding literature and the growing body of research related to this matter have naturally resulted in the need for literature reviews and surveys. Towards the end of the year, the number of literature review studies has also grown exponentially to a similar extent. Many researchers surveyed and reviewed Covid-19 applications from various perspectives and at different scales. Thus, we abstain from repeating what was already reported in the literature. Instead, we propose to build on these reviews to draw conclusions and synthesis. Our aim is not to show the exhaustive applications of AI in battling against Covid-19, the existing reviews already provide valuable insight into this matter. At this stage, giving the number and variety of review papers, we believe that a logical next step and a valuable contribution would be to provide interested researchers a centralized entry point where they can quickly gain a holistic outlook on the emergent literature without having to go through the whole state-of-the-art reviews. Evidently, such comprehensive analysis requires reviewing, comparing, and synthesizing existing review studies, which is currently missing from the literature to the best of our knowledge. The idea of looking at reviews as objects of research rather than original research is a unique approach that differentiates our work from existing reviews on the issue. To systematically bring together, appraise, and summarize the results of related review studies, we adopted the umbrella review as a methodological tool to conduct our study. Umbrella review refers to a review compiling evidence from multiple reviews into one accessible and usable document (Hartling et al., 2014). This method converges perfectly with our goal. It collates evidence from many reviews and offers a "one-stop shopping" synthesis. It also serves as a comparison tool to highlight similarities and differences across reviews, to identify gaps in the evidence, and to determinate priorities for future research. Therefore, the overall purpose of our umbrella review is to provide scholars with a review of the trends and findings of review studies focusing on AI applications in Covid-19. We are particularly interested in identifying clusters of research at two levels, (i) the form level, by analyzing the review procedures, methods, and bibliometric information. And (ii) the content level, by scrutinizing the findings of the reviews and trying to organize them into a unified taxonomy of the reported AI applications.

The second objective of this review is to provide a sort of horizon scanning of the AI landscape based on the interpretation and synthesis of the gathered information. Taking a holistic look at where AI is positioning now in the Covid-19 battlefield should reveal research avenues for the future. Our goal then is to best inform researchers which research directions might be most

[1] https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19—11-march-2020

worthwhile to study. At the present time, it seems vital to project, anticipate, and plan the future of AI. The world on the other side of the crisis will surely look different in many ways economically, socially and health wise (Sharfuddin, 2020), understanding the changes ahead can help us take steps now that are aligned with the world beyond the pandemic. After one year of the black swan event, we believe enough material is now available to sift through and put together a construct of a possible trajectory of future research in AI.

■ Research objectives:

The primary goals of the present review are:

- Systematically comparing, evaluating, and synthesizing the results of reviews addressing the issue of AI's role in Covid-19.
- Proposing a horizon scanning for post-pandemic AI research to guide scholars and to help to prioritize research needs.

These initial objectives were supported by a broad research question for the umbrella review geared towards identifying all trends, patterns and conceptualizations used to categorize AI applications in the review studies. Three testable hypotheses were developed from this research question. Details about the research question and hypotheses are given in the next section.

The remainder of this paper is structured as follows. Section 2 exposes the method and the findings of the umbrella review conducted, the findings are presented under two headings: (i) results distilled from the bibliometric indices and (ii) results distilled from the findings of the included reviews. Section 3 discusses potential future directions in the AI research field and organizes them into seven key themes. Section 4 outlines the limitations and the future scope of the present study. Finally, the "Conclusion" section concludes this review.

2. Umbrella review: Review of reviews on ai applications against COVID-19

2.1. Materials and methods

2.1.1. Study planning

2.1.1.1. Research question. The primary research question of this systematic review is "*What are the trend patterns and how findings are organized in review studies with the focus of AI applications in COVID-19?*". We intentionally formulated a research question sufficiently broad to be inclusive of all aspects of analysis, comparison, and synthesis.

2.1.1.2. Search strategy. Our umbrella review follows the rapid review approach, to speed up the review process we limited our search to reviews in English appeared between 01/12/2019 and 01/06/2021 with a focus on large-scale applications of AI. We conducted the review in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009). To identify the studies subject of review, we searched PubMed and Scopus databases, and preprint servers, including arXiv, bioRxiv and medRxiv. Google Scholar was also used as an additional source to identify relevant references. Our search query is formed by the union of the words "COVID-19" and a set of synonym terms. We define "Artificial Intelligence" broadly to encompass the various methods and tools – including those from machine learning (ML), automation, computer vision, and data science. Even though the umbrella review typically includes mainly systematic reviews, this method allows integrating other types of literature studies (Hartling et al., 2014). Thus, in order to capture a large range of works we extended the type of documents to include systematically conducted reviews but also surveys and narrative reviews. The identified search terms were then compiled into a query using the "OR" and "AND" operators (Table 1).

Table 1
Search string applied.

Operator	Dimension	Keyword, alternative keywords and synonyms
AND	Artificial intelligence	Artificial intelligence OR AI OR Machine Learning OR Deep Learning OR Robotic OR Computer Vision OR Data Science OR Intelligent systems OR Computational Intelligence
	COVID-19	COVID OR Coronavirus OR SARS-COV-2 OR 2019-nCoV OR Pandemic OR Epidemic OR Crisis
	Review type	* Review OR Meta-analysis OR State-of-the-art OR Survey

* indicates that we search for all types of review including rapid, scoping, systematic, literature, narrative, critical…etc.

2.1.1.3. Inclusion criteria. After removing duplicates, 315 articles were screened by reading their titles and abstracts. At this stage, the irrelevant papers were excluded based on this information alone. Then, available full texts were read in order to identify eligible reviews. The eligibility criteria were:

1. The article full text is available in English.
2. The article is published or preprint. Gray literature was included since the pandemic is a time-sensitive topic, some of the studies may not yet be peer-reviewed.
3. The article contains a review of multiple articles or a survey on the state-of-the-art. As mentioned before, we concentrated on the content of the reviews, rather than the accuracy of the review's procedures and methods.
4. The article covers one or many AI methods.
5. The article focuses on the role of AI to tackle the Covid-19 crisis at a large scale, it is not devoted specifically to one Covid-19 application. For example, works like "Artificial Intelligence Applications for COVID-19 in Intensive Care and Emergency Settings: A Systematic Review" (Chee et al., 2021) that reviews the role of AI solely in acute care settings, were not studied in this umbrella review.

As result, out of the 571 articles that were first identified, we evaluated 91 and found 45 reviews meeting our criteria. To avoid bias and to ensure that all relevant and eligible reviews were selected, two authors independently used the search strategy to screen studies for inclusion in the umbrella review. Any disparity was resolved by involving a third reviewer (ML). Fig. 1 shows an overview of the search and selection process. The full list of included reviews is available in the appendix.

2.1.1.4. Data extraction. In order to address the research question and hypotheses, we studied each of the included reviews and extracted data mainly related to:

(i) Bibliometric information,
(ii) The AI methods being investigated,
(iii) The Covid-19 applications being covered,
(iv) The reviews main findings.

Finally, the extracted data were critically analyzed, thoroughly organized and compared, and then synthesized and compiled in (1) findings related to the form of the reviews and (2) results distilled from the contents of the studies. As we have done for the review inclusion, to avoid bias, data extraction was also conducted

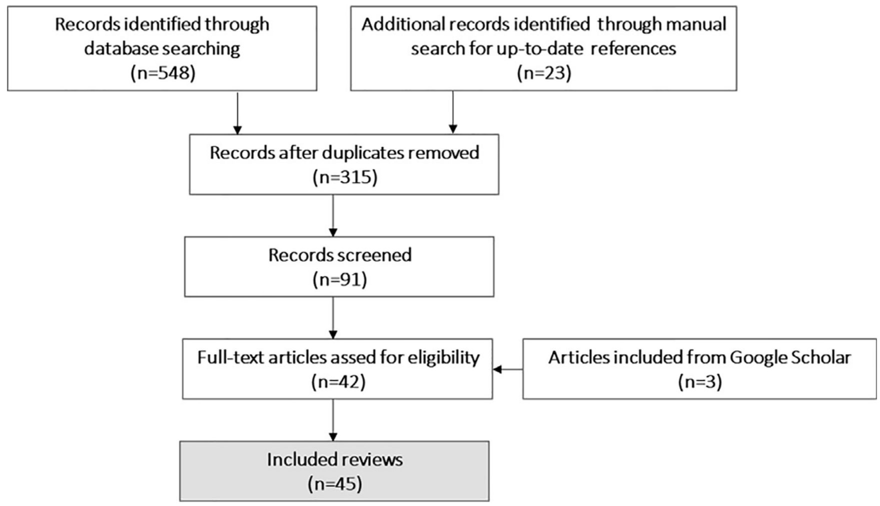

Fig. 1. Flowchart of the selection process of the included reviews.

independently by two different authors (AA and SN). Discrepancies were resolved by discussion, where an agreement could not be reached, the third author was consulted.

2.1.2. Data analysis

2.1.2.1. Main hypotheses. In compliance with our research question and objectives, we aim to test three main hypotheses:

(1) The impact of reviews addressing the issue of AI in Covid-19 is influenced by the study design and bibliometrics. (H_1)
(2) The medical theme is dominating AI applications. (H_2)
(3) The DNN algorithms are dominating the type of AI method being used. (H_3)

2.1.2.2. Primary outcome variables. Based on the defined hypotheses, the outcome variables are defined as follows: (i) number of citations, (ii) sample size, and (iii) frequency of co-occurrence, to measure the review impact in H_1. (iv) Type of study's conceptualization, to measure the medical dominance in H_2. And (v) Type of AI method to measure the dominance of deep architectures in H_3.

The explanatory variables are mainly descriptive information or characteristics of the studies that might influence the effects of interest, such as literature type, review type…etc.

2.1.2.3. Statistical tests. In respect of the first hypothesis, to evaluate the impact and significance of the differences in the bibliometric parameters of the included studies, we used independent *t*-test as a statistical test, p-value was used to assess significance. $p < 0.05$ was considered significant. Specifically, we used a two samples independent *t*-test (two tailed) to understand whether the sample size differed based on the type of the review (i.e., the outcome variable is "sample size" and the explanatory variable is "review type", which has two groups: "Methodological" and "Informal"). The same statistical test was performed to examine how citation count is influenced by the review type and the literature type, respectively.

The hypothesis testing of H_2 and H_3 involves one categorical variable (type of study's conceptualization and type of AI method, respectively) and one group class (all the included studies and all the identified applications, respectively). Thus, we chose to use Chi-Square Goodness of Fit Test to measure of how much the frequency distribution of the conceptualization types and AI method types deviate from a theoretical equitable distribution. we set $\alpha = 0.05$ as a significance level.

The statistical calculation was performed with R version 3.6.1 software for windows and MS Excel version 2016, keywords clustering was performed with VOSviewer version 1.6.16 software for windows.

2.1.2.4. Data reporting. A descriptive approach was used to report the key results of the data analysis. Fundamental features and findings of the included reviews were synthesized narratively, supported by graphics and charts to facilitate interpretation and to highlight key evidence. Statistical findings illustrations include co-occurrence network developed to illustrate the keyword clusters. Box plot used to present different ranges of the study's sample size. Data related to research question characteristics was converted into a stacked bar chart for better visual interpretation. And a Venn diagram was built to illustrate the connectedness of review conceptualizations and highlighting the degree of overlap between them.

2.2. Findings

2.2.1. Bibliometric analysis

2.2.1.1. Grey literature. The analysis of the bibliometric indicators has revealed some interesting trends and patterns. While analyzing the literature growth, we note a weak presence of grey literature in the studied reviews. As can be seen in Table 2, only 9 (20%) of the 45 reviews were unpublished, yet the number of citations is high (a total of 191 citations, an average of 21 citations per review). We speculate this could be a sign that the urgent need for rapid results that marked the first period of the pandemic and which resulted in the rapid growth of scientific production, much of which was non-peer-reviewed works, started decreasing slowly after one year of the health crisis.

Furthermore, given the lengthy process of reviewing surveys and review studies, most of the included published literature has just been published a few months ago. However, the high number of citations indicates that this literature has already been largely cited before being published (a total of 1401 citations, an average of 40 citations per review). Hence, we could claim that many of the current published studies owe their impact to their non-peer-reviewed version. For instance, according to google scholar,

Table 2
type of the included literature.

Type of the literature		No. of Articles		No. of Citations*
Grey literature	Conference proceedings	2	9 (20%)	191
	Preprints	7		
Published	Article	33	36 (80%)	1401
	Book chapter	3		
Total		**45**		**1592**

→ Significant difference in the number of citations was observed between the two subgroups of the literature type (p = 0.0312, *t* test).
* The number of citations as of June 9th, 2021.

Table 3
type of reviews.

Type of the review		No. of Articles	No. of Citations	Date of the first publication*
Methodological reviews	Systematic Literature Review	8	276	August 2020
	Rapid Review	3	494	April 2020
	Scoping Review	4	17	September 2020
	Meta-Analysis	1	13	October 2020
	Bibliometric Study	2	8	November 2020
Total		**18**	**808**	
Informal reviews	Literature survey	13	279	May 2020
	Literature review	14	505	April 2020
Total		**27**	**784**	

→ No statistically significant difference in the number of citations was observed between the two subgroups of the review type (p = 0.2594, *t* test)
* The date of publication was not applied for non-peer-reviewed articles. For the published reviews we used the online publication date when it is available (the Epub date index of PubMed).

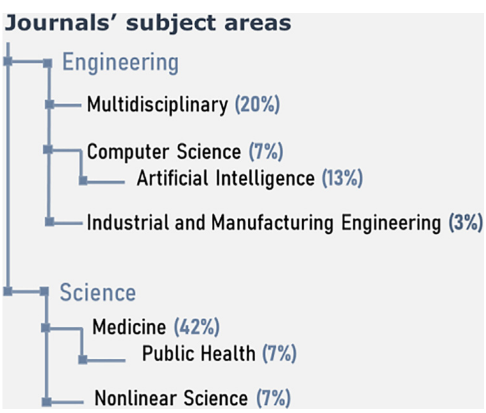

Fig. 2. Journals profiling according to the covered subject areas.

Table 4
Research questions analysis.

Goal	The research questions and/or aims target one or more of the following goals: ■ Identify (I) (overview, explore, investigate) ■ Analysis (A) (examine, evaluate) ■ Synthesize (S) (summarize)
Scope	The research questions and/or aims cover one or more of the following scopes: ■ Potential research to be conducted **(PR)** ■ Current state of research **(CRS)** ■ Promising future research **(PFR)**
Scale	The research questions and/or aims focus on one or both of the following issue's aspects: (1) **Technological Aspect (TA):** What AI methods are used? ■ are they Algorithmic related Methods (**AM**)? ■ or Data related Methods (**DM**)? ■ or both? (2) **Pandemic Aspect (PA):** What facet of Covid-19 pandemic is addressed while using these AI methods? ■ is it a Medical Facet (**MF**)? ■ or General Facets (medical, economic, social…) (**GF**)?

the preprint survey of Pham et al. (2020) that was available since April 2020 counts 68 citations, while its published version was cited 30 times after being published in July 2020.

2.2.1.2. Typology of reviews. Table 3 describes the typology of the studied reviews. Based on how the reviews present themselves and how they describe the methodology aspect, we classified the reviews into two categories: (i) Methodological reviews that encompass systematically conducted reviews, and (ii) Informal reviews that include literature surveys and reviews that do not specify any method used to conduct the study. The review of the body of research regarding AI application to fight Covid-19 was first made through informal reviews. The very first study in this category was available in April 2020 and characterized itself as an early review aiming to encourage researchers to use AI to respond to the sudden crisis (Naudé, 2020a; Naudé, 2020b). The same author continued his call for action in another review published in the same month, where he asserted the importance of overcoming constraints related to the lack of data in order for AI to be impactful against Covid-19 (Naudé, 2020b). In the methodological category, first contributions were made in form of rapid reviews, later other types of systematic reviews were conducted. Although methodological reviews are increasing in number and in impact (number of citations). To date, informal reviews still the most frequent. Moreover, there is a noticeable lack of methodological reviews with aggregation and synthetic aim (e.g., *meta*-analysis and scoping reviews). Specifically, we found *meta*-analysis studies to be the lowest represented study design (1 review only). The lack of research works in the first stage of the pandemic could be the reason behind the scarcity of this type of study. Now, with the availability of a substantial number of research works to support the implementation of *meta*-analyses, we should expect more reviews of this type. The presence of such studies signals the maturity of the body of research and allows researchers to draw conclusions and to define research avenues for the future.

2.2.1.3. Journal profiling. Journal profiling was made using the "subject areas" index of Scopus. As shown in Fig. 2, most of the journals publishing reviews of AI applications for Covid-19 fall into the specific areas of medicine or multidisciplinary engineering, relatively less publications were made in AI or computer science

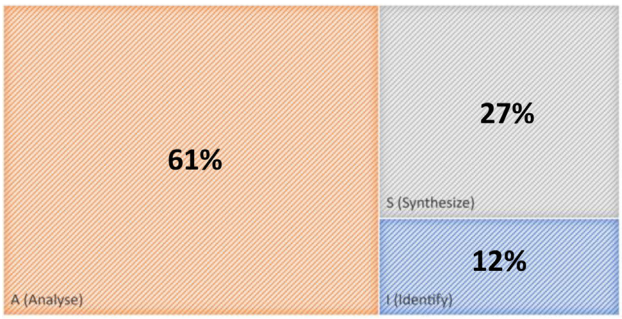

Fig. 3. Goal distribution of research questions.

focused journals. This is likely to mean that the issue is mainly tackled from a medical perspective.

2.2.1.4. Research questions analysis. Since we are studying review articles, two review-related parameters should be analyzed, namely (1) research questions and (2) the size of the studies.

First, methodological and informal reviews were screened to extract their research questions and aim/objectives, respectively. The set of identified questions was then analyzed and compared in order to identify patterns. We found that generally, the research questions revolve around the issue of examining valuable AI research contributions during the pandemic. However, they differ in (i) the goal, (ii) the scope, and (iii) the scale of the act of examining. Table 4 explains these differences. In terms of goal, each review aims either at identifying, analyzing, or synthesizing the role of AI. In terms of scope, research questions generally cover research not yet undertaken and that should be activated, study contributions that have been already undertaken and evaluate them, or define new futurist research to be undertaken in the next phase. These scopes illustrate the early, the amid, and the post phases of the pandemic, respectively. In terms of scale, research questions focus either on the pandemic aspect (e.g., the health response, the economic implications of the pandemic) or the technical aspect (i.e., the algorithms and data being used to fight the pandemic), some reviews focus on both aspects. Table 4 provides some abbreviations related to the research question components that will be used in the remainder of this section.

After indexing each review with the corresponding goal, scope, and scale, we draw the following conclusions, illustrated in Figs. 3–5 and Table 5, respectively:

(i) Most of the existing reviews in the literature (61%) focus on "analyzing" the AI contributions in response to Covid-19 without providing much "synthesis" on the matter (Fig. 3). (ii) The scope of most reviews covers AI application during the pandemic (scope = CRS). Among these studies, some works enlarged their scope to cover futuristic approaches that can help managing the situation at the pandemic's next stages or even after the pandemic's end (scope = CRS + PFR) (Fig. 4). (iii) The scale of the majority of the reviews is oriented towards pure medical (public health) applications. Among the 45 surveyed reviews, only 7 reviews chose to address the issue from a global perspective or through the lens of the technical perspective (Fig. 5). To further the analysis, we combined the three components of the research question (goal, scope, and scale) and projected the result on the time axis, in order to analyze the evolution of the objective of the reviews over time (Table 5). In doing so, some patterns emerged.

First, most of the current reviews fall under the combination (goal: A, scope: CRS, scale: PA: MF), which means that existing reviews mostly follow the objective of analyzing the current situation from a medical perspective. Second, naturally the goal "Identify" is correlated with the scope of "Potential research to be conducted". However, at this level of the research maturity regarding the issue, we expected that this goal would also be correlated with the scope of "Promising future research". However, this scope was only relatively covered by studies with the goal of "Analysis" and "Synthesize". In fact, even for these reviews, the focus was essentially on the examination of the current situation. Generally, the future of AI research is only discussed in the conclusion, in form of recommendations or learned lessons. For instance, Nguyen and Nguyen (2020), presented his work as a survey and future research directions. His work was divided into three parts, the first one analyzed the AI applications right up to the date of the study, the second investigated Covid-19 data sources. It is only in the third part "the conclusion" that the author pointed out promising AI methods that can be used to solve the problems observed. Within the set of the included reviews, no study has focused exclusively on the scope of "Promising future research" as can be seen in Table 5. Third, the general perspective (scale: PA:GF) was only adopted by reviews with a "Synthesize" goal, among the 61% reviews seeking to analyze and evaluate AI applications, or the 12% reviews aiming to identify where AI could beneficially be used, no study has covered application areas outside the health system sphere. Fourth, except for some individual studies, three milestones marked the evaluation of the reviews' objective over time. Early surveys aimed to identify and explore potential AI research to be conducted urgently in order to respond to the crisis. These reviews were published generally in the first half of 2020 and they are annotated with the combination (goal: I, scope: PR, scale: PA:MF [TA]). Then reviews with the objective of analyzing and evaluating the contributions that have been made started taking place. This line of works was reinforced by systematically conducted reviews that rigorously analyze evidence from research studies to spot trends to follow and pitfalls to avoid. These reviews were published generally in the second semester of 2020 and they are annotated with the combination (goal: A, scope: CRS, scale: PA:MF [TA]). At the beginning of this year, the objective started to change towards more knowledge synthesis. Indeed, as many reviews have been studied the issues, recent studies tried to distinguish their work by proposing improvement comparing to precedent vague of reviews, by being comprehensive or detailed,

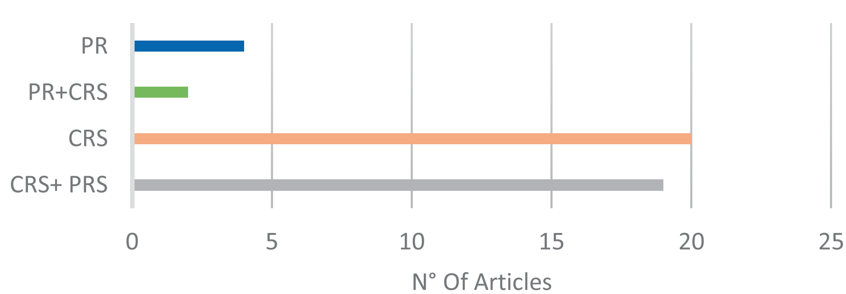

Fig. 4. Scope distribution of research questions.

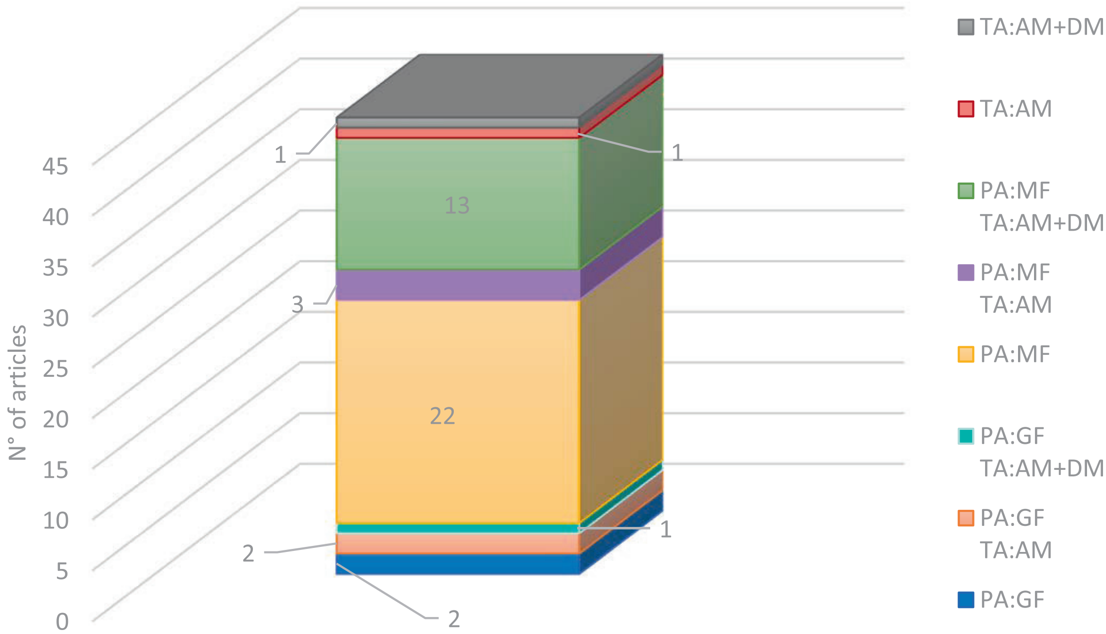

Fig. 5. Scale distribution of research questions.

Table 5
research questions' evolution over time.

				2020									2021				
Goal	**Scope**	**Scale**	**N° of Articles**	**Apr**	**May**	**Jun**	**July**	**Aug**	**Sep**	**Oct**	**Nov**	**dec**	**Jan**	**Feb**	**Mar**	**Apr**	**May**
I	PR	PA:MF	3														
	PR	TA:AM	1														
	CRS+PR	PA:MF TA:AM+DM	1														
A	CRS+PR	PA:MF	1														
	CRS	PA:MF	11														
	CRS	PA:MF TA:AM+DM	3														
	CRS	TA:AM+DM	1														
	CRS+PFR	PA:MF	3														
	CRS+PFR	PA:MF TA:AM+DM	5														
	CRS+PFR	PA:MF TA:AM	3														
S	CRS	PA:GF TA:AM	2														
	CRS	PA:MF	2														
	CRS	PA:MF TA:AM+DM	1														
	CRS+PFR	PA:MF TA:AM+DM	3														
	CRS+PFR	PA:GF TA:AM+DM	1														
	CRS+PFR	PA:GF	2														
	CRS+PFR	PA:MF	2														

by adopting a more global perspective instead of a medical specific perspective, or by focusing only on latest results and achievements. These reviews are generally annotated with the combination (goal: S, scope: CRS + PFR, scale: PA:MF/GF [TA]). Some reviews do not evolve according to this pattern. Reviews (Nadeem et al., 2020) and (Tseng et al., 2020), with a goal of identifying potential research to be conducted, were published late in the year 2020. These reviews tried to address some limitations observed in what the precedent reviews have identified. Review (Nadeem et al., 2020) suggested that AI can be of great significance in the fight

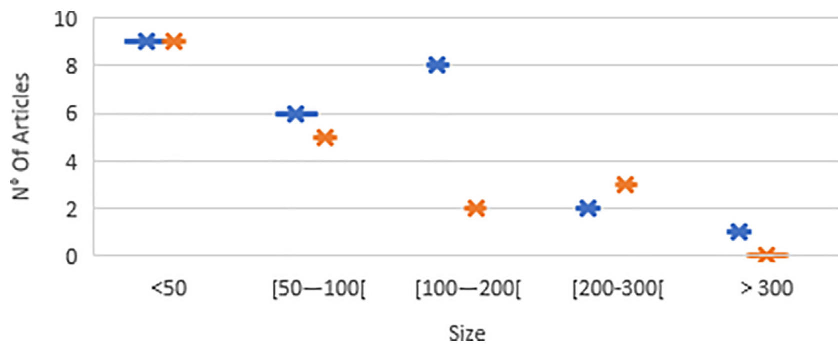

Fig. 6. Size of the included reviews → Significant difference in the sample size was observed between the two subgroups of the review type (p = 0,0493, *t* test).

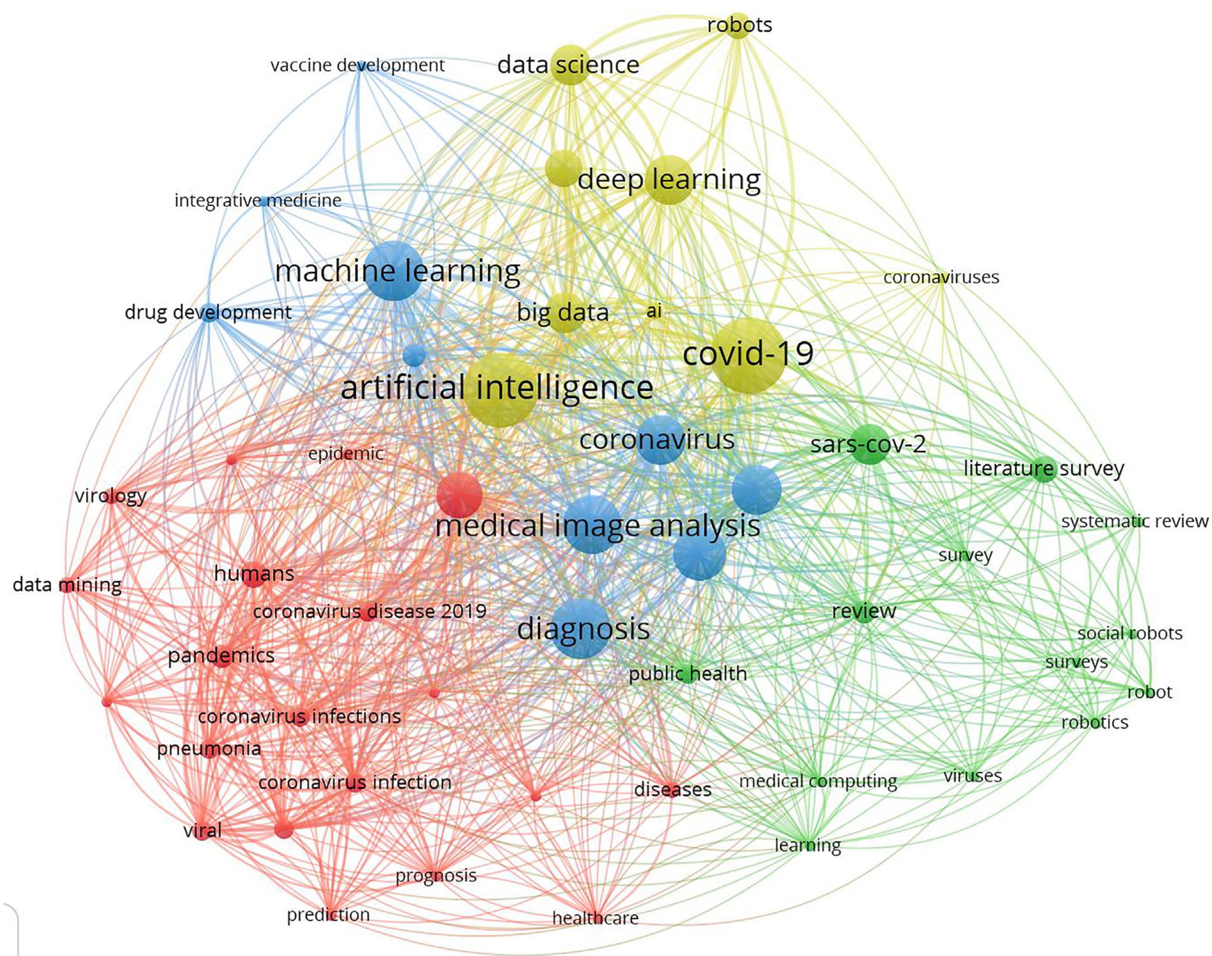

Fig. 7. Keywords mapping of the included reviews.

against Covid-19 combined with other forms of technology like the Internet of Things (IoT), and identified accordingly IoT based AI methods that can aid in winning this battle. Review (Tseng et al., 2020) claimed that although there is so much effort conducted to studying how AI could be beneficial to combat Covid-19, the literature did not shed any light on the specific issue of applying computational intelligence in the battle. To fill this gap the review identified key pandemic issues that could be resolved with this type of techniques. On the other hand, reviews (Fong et al., 2020) and (Bansal et al., 2020), published early in the second semester of 2020, can be considered one of the first initiatives that attempted to synthesize the literature around AI applications against the pandemic. The first one adopted a structural approach to synthesize the utility of AI in four fundamental benefits (1) autonomous everything, (2) pervasive knowledge, (3) assistive technology, and (4) rational decision support. In the other review, AI utility was synthesized from a temporal viewpoint using a narrative approach (before the pandemic, and amid the various stages of the pandemic).

2.2.1.5. Sample size analysis. After analyzing the research questions, we conducted a sample size analysis. The size of the methodological reviews was retrieved directly from the articles based on the selection process information. For the informal reviews, in the case where the number of the studied works was not explicitly mentioned, the size was estimated based on the citing works. As depicted in Fig. 6, the sample sizes varied from study to study, ranging from less than 20 to more than 300. As expected, the size of the studies grows proportionally with time. A recent review (Syeda et al., 2021) published in January 2021 reviewed 128 works on the issue, while an earlier one (Islam et al., 2020) conducted in June 2020, surveyed only 35 works. The size also depends on the type of the review (narrative, rapid, or systematic). As shown in Fig. 6, informal reviews surveyed relatively more works comparing to methodological reviews bound to respect a rigorous process of selection (An average size of 126 references for informal reviews and 77 works for mythological reviews).

2.2.1.6. Keyword analysis. Finally, in the keyword analysis, four broad thematic areas of Covid-19 research reviews were identified. Fig. 7 shows the connected network of the most common keywords used by authors and indexed in Scopus. The keywords related to Covid-19 and AI are naturally located in the center of the words map. As can be seen, different sub-domains are found to be clustered around these two terms. The cluster of AI methods includes mainly the following terms that had several co-occurring keywords: deep learning, robots, big data, and data science. The cluster of AI applications shows a focus on clinical settings related use of AI such as drug discovery, diagnosis, and medical image analysis. The map is also surrounded by keywords highlighting the review methods such as systematic review, literature survey, review, and other terms. The last cluster represents keywords related to the pandemic's virologic background (virology, pneumonia, coronavirus infection...).

As a conclusion, the key observation that could be drawn from this bibliometric analysis is the dynamic of the line of work aiming at surveying the role of AI to fight Covid-19:

- An unprecedented growth of production marked by a high number of reviews and a high number of citations. For the sake of comparison, we used the following simplified queries to collect AI related reviews from Scopus with the focus of COVID-19 and radiology, respectively. (**Query1***: TITLE-ABS-KEY ("COVID-19″) AND TITLE-ABS-KEY ("Artificial Intelligence") AND DOCTYPE (re)* , **Query2**: *TITLE-ABS-KEY ("RADIOLOGY") AND TITLE-ABS-KEY ("Artificial Intelligence") AND DOCTYPE (re)*). Surprisingly, the two queries share the same number of results. The number of reviews intersecting AI and Covid-19 on Scopus is almost the same number of results obtained from the same database when looking for AI applications in a medical domain as popular as radiology without any time limit. By May 20th, 2021, *Query 1* returned 212 documents with over one hundred citations for only a year of research. *Query 2* returned 214 documents with 4734 total citations for over thirty years of research. This denotes the great and intensive involvement of the AI scientific community in the fight against the novel disease. This also shows that Covid-19 has given a green light for AI to unleash its full power without barrier.
- The dynamic is also seen through the rapid evolution of the research questions addressed. In a window of one year, reviews and surveys started from identifying potential AI applications, then analyzing the contributions made, and finally evaluating and synthesizing the situation. Though, we observed that so far not yet many reviews are focusing on the synthesizing question.
- Arguably, this dynamic could in part be explained by the urgent nature of the pandemic matter. Which sometimes led to sacrifice accuracy and rigor for urgency. It is true, that currently, most of the identified literature is peer-reviewed and published. However, it has been noted that the number of informal reviews is relatively high compared to methodological reviews, and even systematically conducted reviews tended to implement their methods with agility and flexibility in order to accelerate the achievement of results.

Apart from the dynamic of the field, a recurrent observation throughout this analysis, which needs to be further investigated, is the focus on medical-related applications in addressing the issue. This observation was derived from the analysis of the type of journals where the reviews were published, the scale of the reviews 'research questions, and the clusters identified in the keyword analysis. In the next section, we will dig further into the reviews' content and findings to understand more about the reasons behind this trend.

2.2.2. Taxonomy of taxonomies. The surveys and reviews covering AI applied to Covid-19 vary mostly in how they organize Covid-19 applications. Each work comes with varying conceptualizations and taxonomies. In this section, we propose to systematize these multiple angles of view in one unified canvas. In compliance with our goal, we do not intend to seek every way that AI approaches have been employed. Rather, we aim to synthesis knowledge regarding the way researchers have identified and classified these applications. To this end, we tried to compile the existing classifications into a sort of *meta*-taxonomy or taxonomy of taxonomies. This *meta*-taxonomy is described in Fig. 8 and detailed further in the following sub-sections. Based on the study of the findings of the scanned body of literature, we distilled five main strategies adopted by the reviews to organize Covid-19 applications. (i) Studies depicting Covid-19 applications under a certain point of view, namely Perceptual Studies. (ii) Studies focusing on the health response which classify AI's uses according to their clinical/epidemiological aim, namely Medical Studies. (iii) Studies highlighting the importance of context in categorizing Covid-19 applications, namely Contextual Studies, (iv) Technical Studies that base their conceptualization on a taxonomy of AI methods. And (v) Hybrid Studies that unify medical and technical strategies.

(1) Perceptual studies

Different ways to perceive the issue lead to different ways to address it. Each review of this class has proposed a taxonomy based on a specific perception.

Reviews (Shen et al., 2020; Wang and Wang, 2021) adopted a task-oriented perception to classify AI applications. They provided an overview of the robotic achievement based on the desired tasks. Many forms of robots have been employed (e.g., stationary Manipulators, drones, wheeled robots, mobile manipulators, desktop robot, and social robots) to perform autonomously and safely routine tasks that conventionally require large amounts of human labor, such as disinfection, monitoring, diagnosis, nursing, surgery, delivering, telepresence, logistic, and manufacturing tasks. Based on the pandemic experience, both reviews argued that the progress of the robotic field is dependent on the development of some supporting technologies including sensor technologies, 5G, IoT, image processing, HRC, and Haptic control.

Review (Islam et al., 2020) chose to survey existing research in terms of their purposes. According to the results of this systematic review, AI methods are used to detect, predict, identify, classify, and compare. Similarly, review (Abd-Alrazaq et al. 2020) has identified five purposes, namely: AI for diagnosing, for treatment and vaccines, for epidemiological modeling, for patient management, and for infodemiology.

Some reviews like (Kumar et al., 2020; Fong et al., 2020; Raza, 2020) break down the AI applications by perspectives or targets. Some of the identified perspectives are: patient's perspective, com-

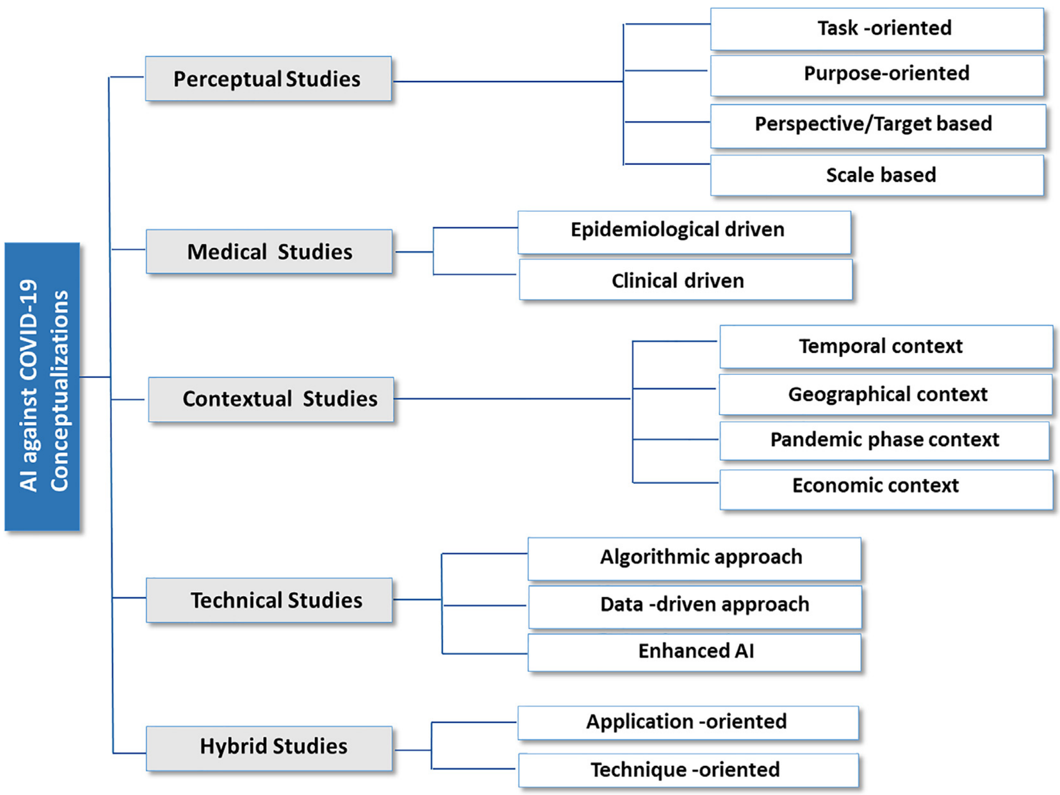

Fig. 8. Taxonomy of AI applications taxonomies.

putational biology perspective, heath system perspective, economic perspective, and social perspective.

Finally, review (Bullock et al., 2020) proposed a multi-scale perception. Inspired by the digital in-toto reconstruction of living organisms, the authors categorized AI applications in three scales: the molecular scale, the clinical scale, and the societal scale.

(2) Medical studies

This class encompasses reviews that captured medical related applications, which means that the focus is put not on the AI tools being used, but rather on the results of their application in medical settings. The collated medical applications are either (i) epidemiological driven or (ii) clinical driven. Epidemiological driven reviews (Syeda et al., 2021; Enughwure and Febaide, 2020; Bansal et al., 2020) focus on applications in relation to the virological nature of the disease, such as outbark prediction, forecasting, epidemiological modeling, biomedicine analysis, protein structure, and drug discovery and repurposing. While clinical driven reviews (Vaishya et al., 2020; Naudé, 2020a; Chen et al., 2020) are interested in uses in clinical scenarios including diagnosing, screening, patient management, hospital resources management, healthcare workers safety and workload reducing, clinical decision-making, and treatment. Sometimes, overlaps are observed between the two categories. Particularly applications related to drug development tend to appear in both categories (Jiayang Chen et al., 2020; Bansal et al., 2020). They belong to the first sub-class as being part of the epidemiological management process, but they are also part of the clinical applications since they fall within the scope of disease therapies and treatment.

(3) Contextual studies

Contextual reviews reflect the impact of the context in studying AI uses against the pandemic. Based on the surveyed reviews, we identified four contexts that have been studied in the literature, namely: (i) the temporal context, (ii) the geographical context, (iii) the pandemic phase context, and (iv) the economic context.

According to the contextual reviews, the utility of AI methods changes when the context change. For instance, review (Islam et al. ,2020) compared works conducted in a specific region and region-independent articles. The authors found that contextual articles focused mainly on epidemic forecasting and sustainable development (because such applications need contextual data), while most of the disease detection related articles are not context-sensitive.

An early review (Bragazzi et al., 2020) proposed a roadmap of AI applications in the short term, medium-term, and long term. Its findings showed that as time passes, AI uses will change from diagnosis and prognosis in the immediate term, to identification of a potential therapeutic option in the medium-term, to enhancing smart and resilient cities over the long run. A very recent review Piccialli et al. (2021) adopted the same categorization by framing the problem as a timeline, obtained by reorganizing the pandemic's temporal phases, as provided by the WHO. Namely, before the pandemic, at the verge of the pandemic, before and after the first peak, and after the pandemic.

Review (Bansal et al., 2020) categorized AI applications according to the stage of a pandemic, they described six phases tracing the evolution of a pandemic transmission modes, from animal-to-animal to human-to-human transmission, passing by animal-to-human transmission. Additionally, "Post Peak" and "Possible New Wave" stages were included to illustrate the peak outbreak of the pandemic, and finally, the post-pandemic period closes the pandemic process, it corresponds to the period where the disease has stabilized and returned to seasonal influenza level. The authors showed that AI for outbreak detection will be used across all the pandemic stages. Preventive strategies and vaccine development will take place after confirming a possible animal-human transmission. Early case detection and tracking are necessary once a community-level outbreak has been identified. However, not much insights have been given for the post-pandemic period.

Review (Naseem et al., 2020) argued that most AI-driven tools are seen to be reinforced and practiced in high-income countries. While in low middle-income countries, there is still a lack of evidence on the use of AI in managing the Covid-19 pandemic. Thus, the authors proposed to conduct their scoping review through the economical context lens, their results showed that AI use in developing countries can help in eradicating health inequalities and reduce the burden on the health care systems.

(4) Technical studies

Some reviews preferred to organize their work based on the AI methods that have adopted. Generally, one or more of the following AI areas have been covered.

(i) Algorithmic approaches. Many reviews focused on the algorithmic aspect of AI. Review (Tseng et al., 2020) based its investigation on a categorization of computational intelligence, while Shorten et al. (2021) considered their work as the first survey viewing Covid-19 applications solely through the lens of Deep Learning. Review (Ulhaq et al., 2020) covered computer vision applications. Review (Hussain et al., 2020) illustrated the use of ML techniques. And review (Shen et al., 2020) reported on efforts made by the robotic community - Just to name a few.

We recorded each AI method that has been reported by these reviews to assemble a complete picture of the extent to which algorithmic approaches have been used amid the pandemic.

- Commonly used **traditional machine learning** algorithms are Support Vector Machines, fuzzy logic system, Random Forests, Decision Trees, Logistic Regression, and Ensemble Machine Learning.
- Most occurred **deep learning** architectures (DNN) in the included reviews are Convolutional Neural Networks (CNN), Generative Adversarial Networks (GAN), Recurrent Neural Networks (RNN) notably Long /Short Term Memory (LSTM), Extreme Learning Machine (ELM). In addition of some hybrid forms of deep learning (e.g., CNN-SVM, deep ensemble algorithms).
- **Computer vision** is hugely supported and powered by deep learning, most the models used are CNN and its variants (e.g., SqueezNet, ResNet, AlexNet, Google Net, and VGG Net), pre-trained networks, gray level co-occurrence matrix. In addition to data augmentation (using GAN) and transfer learning (notably fine-tuned deep transfer learning) which are used to manage small datasets.
- AI techniques related to **Natural language processing** (NLP) have also been remarkably used, such as Continuous Bag of Words model, Skip-gram models, Embeddings from Language Models (ELMo), and Porter Stemming.
- **Robot** types that have been mostly used are collaborative and social robots, stationary and mobile manipulators, drones, arms and wheeled robots.
- Finally, we noted that there is a considerable focus on **comparing algorithms** to find the best one for a particular application, some of the used metrics include Accuracy, Specificity, Sensitivity, Positive predictive value (PPV), Negative predictive value (NPV), Area Under Curve (AUC), and F1 score.

(ii) **Data-driven applications.** Data are central to all medical care in general, and they are particularly vital for managing Covid-19. We analyzed reviews reporting on the data aspect and compared their results in terms of data types, sources, size, and corresponding AI methods.

- A broad range of data types have been used in pandemic and allied applications. They range from textual data to numerical measurements, images, and sound. (i) Textual data encompass (a) narrative data gathered from patient's description and information, (b) clinical data gathered from hospitals, electronic health records (HER), and laboratory data, (c) embedded sensor data used in telehealth and include mobility data, physiological vital signs, and various other movement-related signals, (d) biomedical data such as viral genomic and proteomic sequences, (e) demographic and environmental data, (f) guidelines and scholarly articles, (g) mobility data and social media content. (ii) Numerical data include mainly epidemiological data in form of numerical time series data of infection cases. (iii) Image data are formed mainly by two medical imaging modalities chest X-ray and CT. (iv) Sound datasets contain mainly cough and breath sounds employed to diagnose Covid-19.
- To gather such data, researchers and practitioners rely on the following sources: public databases, clinical settings, government sources, literature, social media, migrated data (e.g., data from 2003 SARS epidemic data or from other countries), and open data science competitions established to promote research in this area. In this regard, most of the authors call for an urgent need to share publicly and openly Covid-19 data.
- Data size is not always reported in the studied works, but reviews that investigated this feature noted that the number of samples is still comparably small (less than 1,000 in half of the research studies according to (Abd-Alrazaq et al., 2020)).

Based on the precedent observations, we can assume that the diversity, size, and the lack of publicly available data are the main issues hindering the full potential of data-driven applications.

Furthermore, the AI methods required to analyze Covid-19 related data vary depending on the type of data. For example, numerical time series data are mostly handled with traditional ML methods. Researchers use text mining and NLP tools to explore different aspects of textual data, mainly from social media data. Biomedical data analysis is done using traditional ML, deep learning, or a combination of both (ensemble methods). Similarly for sound analysis, the patterns of coughs and breath can be processed using deep learning or traditional learning algorithms. Medical images are high-dimensional data that require processing capabilities of deep learning and computer vision methods in which CNN-based models are common.

(iii) **Enhanced AI.** In addition to exploring AI applications in battling Covid-19, some reviews furthered their study by surveying how AI combined or enhanced by other technologies could form an added value in the battle. As mentioned before, Nadeem et al. (2020) presented scenarios where AI works in tandem with IoT to provide efficient ways to mitigate Covid-19 impacts. Particularly, IoT-based AI applications can help to enable remote communications, sharing data in real-time, implementing control strategies, and supporting decision making. Hussain et al. (2020) encouraged cloud computing incorporating, they considered

Table 6
Dimensional characteristics of the included reviews.

Apps	Total of Applications (Apps)	Total of distinct apps	Avg App/review	Max. N° of Apps	Min. N° of Apps
	332	65	10	44	3
Breadth	Avg breadth/review	Max. breadth	Min. breadth		
	4	11	2		
Depth	Avg depth/review	Max. depth	Min. depth		
	2	4	1		

Table 7
top 10 of the most reported covid-19 applications in the included reviews.

Application	Frequency	Class of study
Vaccine/Drug discovery and development	77%	All
Diagnosis	66%	All
Social control and surveillance	54%	All
Radiological image analysis	37%	All
Biomedicine/Virology/Pathogenesis	34%	All
Forecasting	34%	all
Survival and risk stratification health	23%	All except one
Deep learning algorithms uses	20%	All except one
Clinical data analysis	17%	All
Natural language processing uses	17%	All except one

AI-oriented cloud computing a vital mean of virtualization for the emergent culture of isolation. They exposed accordingly how virtual networks, servers, storage, middleware, and application can help in continuing living and working safely. Pham et al. (2020) discussed how AI combined with big data showed effectiveness in better understanding the virus and forecasting its outbreak. They also highlighted possible technologies to solve the privacy and security issues in AI applications, namely blockchain and federated learning.

(5) Hybrid studies

The last class of reviews adopted a comprehensive approach in the aim of providing an overall picture full of details. Thus, they are not fully technical, and they do not focus exclusively on the medical aspects. Rather, they try to align both aspects. Hence, we consider them hybrid studies. Depending on their structure, we distinguish between (i) Application-oriented hybrid studies that detailed AI methods under their corresponding Covid-19 applications (Tayarani, 2021). And (ii) Technique-oriented hybrid studies that investigate Covid-19 applications according to core AI methods (Wang and Wang, 2021).

As confirmed by their authors, the challenge facing such reviews is to put, in an organized and comprehensible format, a large number of researches that are hard to put on the same canvas (Tayarani, 2021). Although difficult to be conducted and elaborated, we find such studies very useful in the sense that they provide the key added value of mapping each Covid-19 application to the corresponding AI methods. One of the most extensive studies in this direction is the recent review of Tayarani (2021). Along the Covid-19 applications identified by this review, the author detailed principal algorithms used in each application supported by illustrative research examples. The overview covers mainly

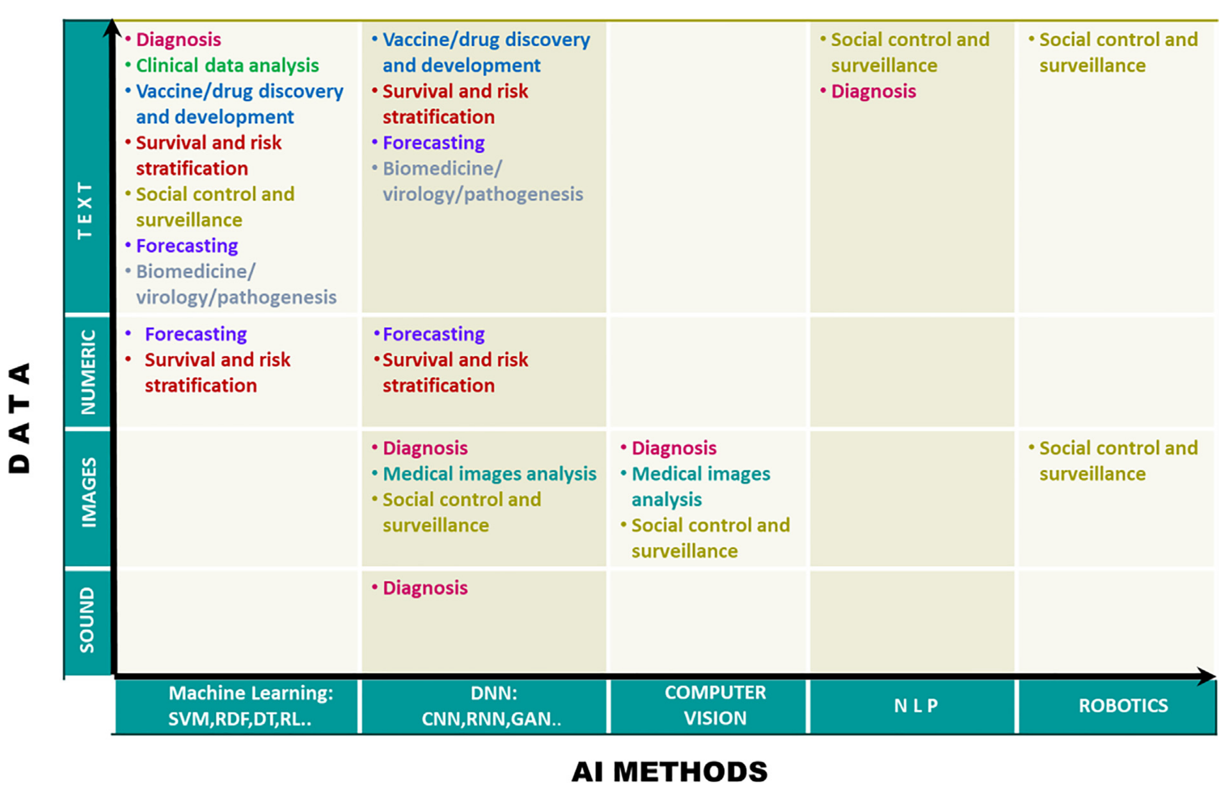

Fig. 9. Mapping of AI applications with data types and AI methods → *Differences between AI method frequencies are significant (p = 0.0003, Chi-Square Goodness of Fit Test).*

medical and public health related applications including diagnosis, monitoring patients, identifying severity of a patient, processing covid-19 related imaging tests, epidemiology, and pharmaceutics. Some effects on human life, economy, industry have also been included as a part of epidemiology related applications. However, the review focused specifically and solely on ML and deep learning, and the data aspect was discussed only a little at the end of the work.

Based on the analysis of the findings of the included studies in general, and the hybrid studies in particular, we tried to build up a synthesis that integrates and maps the three aspects: Data, AI models, and Covid-19 applications. Our aim is to provide the reader with high-level cartography that shows a holistic view of how Covid-19 issues have been articulated for the application of AI. To draw our synthesis, we projected the most reported covid-19 applications in the literature (see Table 7 below) on the two-axis formed by the main previously identified types of data and AI methods. The result is illustrated in Fig. 9. In the following, we provide a brief outline of the cartography illustrated in Fig. 9 by describing the most dominant Covid-19 applications and by precising the corresponding AI tools and data types.

- Since the outbreak of the pandemic, research efforts have focused on finding effective drugs and vaccines. It is mainly ML, DNN, and evolutionary algorithms that have been involved implicitly and explicitly in all the sub-processes of Covid-19 vaccines design and development, including molecular identification, managing clinical trials, and vaccine production and distribution.
- On a similar ground, researchers explored the utility of AI for diagnosis purposes. In fact, this is arguably where most of the first rush of AI initiatives focused on. It includes medical images and clinical data analysis routines. Reverse Transcription Polymerase Chain Reaction (RT-PCR) tests are the key approach used for diagnosing SARS-CoV-2 virus. Models proposed in this vein are generally based on traditional ML algorithms to analyze clinical data. However, RT-PCR faces the limitations of complicated sample preparation, low detection efficiency, and high false-negative rate (Bullock et al., 2020). As such, there is growing interest in alternative diagnostic methodologies which use (i) blood testing methods, (ii) medical imaging, or (ii) non-invasive detection solutions. Many ensemble learning models were proposed for diagnosing Covid-19 from routine blood tests. While CNN and computer vision techniques were mostly used to support Covid-19 diagnosis based on medical imaging inspection including mainly chest X-ray and lung CT imaging. Recently, a number of original non-invasive detection solutions are found in the literature, they are mostly deep learning models that are trained to classify cough sound and identify respiratory patterns. For all these diagnosis modalities, NLP plays an important supporting role in extracting valuable data from the narrative textual data before inputted to ML or deep learning models.
- Despite being the subject to ethics and privacy debates, monitoring is one of the areas where AI is succeeding. Indeed, AI technologies especially robots and computer vision have been widely used in epidemic control and social management, including individual temperature detection, contact tracking, social distancing monitoring, etc. In this vein, social media data and mobility data have played a pivotal role in monitoring and managing infodemic.
- In the epidemiological field, before the recent drug development enthusiasm, AI models have first proved to be more useful for understanding the virus. The origin, classification, and characteristics of SARS-CoV-2 have been analyzed through proteomics and genomic studies using ensemble learning and fuzzy logic systems (Jianguo Chen et al., 2020). Biomedical data in addition to case and demographic data have also been used in forecasting modeling based on RNN models.
- Finally, predicting recovery or mortality and developing risk stratification mechanisms among Covid-19 patients are important to facilitate timely assessments, allocate hospital resources efficiently, and make appropriate decisions. Clinical data such as demographics, laboratory results, and voice signals of people tested positive are fed to ML classifiers, ensemble learning, and deep learning algorithms to derive such risk stratification score system.

At a glance, it is clear that ML and deep learning methods are dominating the AI landscape dedicated to fighting the virus. As for data types, medical images-based data are mostly brought into service for Covid-19 diagnosis. While diverse types of textual data are used for different clinical routines, epidemiological models, and social control.

It is important to note that the classes described in the *meta*-taxonomy are neither meant to be mutually exclusive nor exhaustive. Indeed, having a domain of interest as fast changing as the pandemic make it difficult to be exhaustive. We tried to abstract the present state of thinking. Nonetheless, future works could confirm or complete the proposed *meta*-taxonomy. Moreover, the identified classes reflect different points of view but they are not independents, some of the included reviews belong to multiple classes. In this sense, we furthered the analysis by comparing between the proposed taxonomic classes to see to what degree they overlap and fit to each other, and to determine what are the most adopted conceptualizations.

Comparison has been carried out first by measuring the use of each taxonomic class. As depicted in Fig. 10, the medical studies conceptualization received the most considerable attention from researchers. This confirms the results obtained in the bibliometric analysis. Which means that, to date, AI's best results are mainly observed in applications related to the medical and healthcare implications of the virus. Which in turn could be explained by the high priority attributed to this type of applications amid the pandemic. We believe that it is important to move beyond this dominant conceptualization, and to consider applications out of the medical box in order to be able to evaluate the full impact and contribution of AI in handling explicit and implicit implications of Covid-19. Furthermore, based on the preceding discussion, one might consider using hybrid studies as the reference taxonomy of choice. However, so far, this taxonomic class has not yet been commonly adopted, mainly due to the lack of resources and data to conduct such detailed studies, especially at the pandemic early stages. On the other hand, as the epidemic proceeds, it is unrealistic to expect that AI applications will remain the same for all countries and economies. There is no one-size-fits-all way to address the issue, changing the temporal, the regional, the economic, the social, or the cultural context bring with it insights that determine the relevant model to be adopted. Surprisingly, investigating AI applications through the contextual lens has not attracted a lot of researchers as can be seen in Fig. 10.

In terms of dimension, the 45 included reviews proposed diverse conceptualizations that differ both in breadth and depth. Which reflects the number of the areas of application and the number of applications in a particular area, respectively. The numbers shown in Table 6 indicate a large difference between the reviews in terms of granularity. For instance, Tayarani (2021) identified more than 40 distinct applications, while Ahuja et al. (2020) discussed only three high-level areas of applications. Similarly, some reviews (Wang and Wang, 2021; Raza, 2020) contain only one level of applications, while others (Abd-Alrazaq et al., 2020; Kamalov et al., 2021) go down to the fourth level of granularity. Naturally,

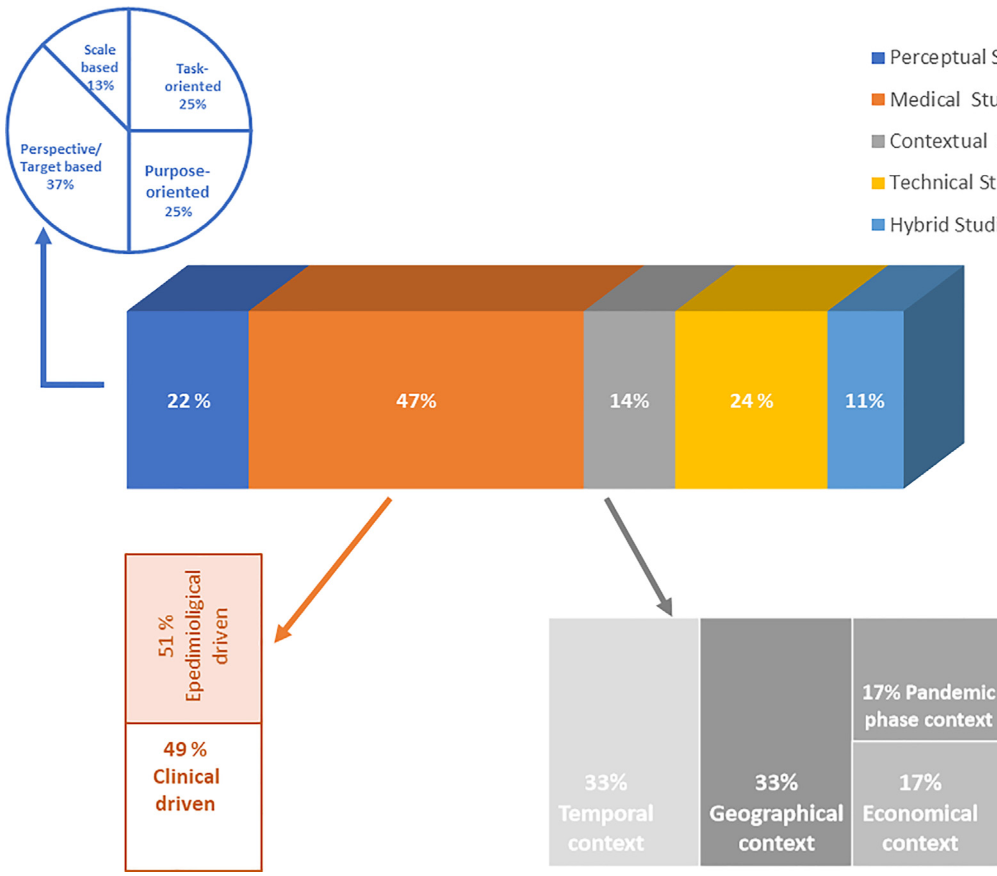

Fig. 10. Distribution of the proposed taxonomic classes → *Differences between studies conceptualization frequencies are significant (p = 0.0008, Chi-Square Goodness of Fit Test).*

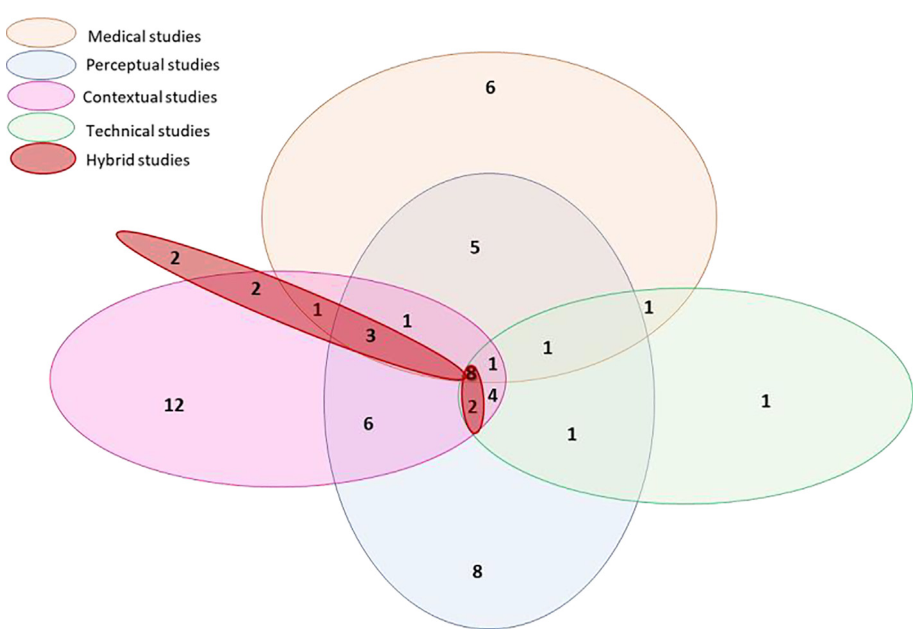

Fig. 11. Similarity comparison between the taxonomic classes.

the type of the review and the time of publication impact the dimension of the conceptualization, but we noted that it is also correlated to the taxonomic class adopted. Generally, technical studies are most granular while medical ones are the broader.

Furthermore, we determined how similar the identified taxonomies (conceptualizations) are to each other by counting the shared applications. The similarity comparison reported in Fig. 11, clearly shows that there are a lot of differences between the five taxonomic classifications, but there is also a lot of overlap, too. Each class has applications not shared with any other classes – 45% of applications are unique while 55% of applications are shared. The contextual and the hybrid studies share many more applications than they have their own applications, indicating that they are much less diverse than other taxonomies. Interestingly, there are not many applications in the intersections that exclude perceptual studies (90% of the shared applications belong to perceptual studies), indicating that the other taxonomies map well on this taxonomic class. Only eight applications (12%) have been reported by all taxonomic classes, indicating that overall, the five taxonomies are not similar, each one is spanning its own spectrum but together they shape well their common research landscape.

Finally, mapping applications between reviews reveals the ten core AI applications. They are applications with the highest frequencies (that have been reported in many reviews), which also coincides with applications that have been cited in all taxonomic classes. As can be noted in Table 7, once again the core applications remain within the medical scope. The lion's share is taken by vaccine and drug development. Never before had we witnessed such a race for the development of a vaccine against a pathogen. Since the pandemic outbreak, finding suitable therapies to address this aggressive pathogen has been a research priority. Hence, it is only natural to find this application at the top list of the most prominent Covid-19 applications. The preponderance of diagnosis applications is comparable to that of vaccine and drug development. It is arguably the most diverse application; it ranges from medical imaging-based diagnosis to non-invasive based diagnosis. Another area of interest is social control and surveillance, it includes initiatives aiming at containing the pandemic, especially at its first phase during the quarantine. Less frequent applications are related to the technical aspects including mainly DNN and NLP uses to handle the health issue.

All in all, the analysis, comparison, and evaluation of the findings of the included reviews, show a clear dominance of medical-related applications. Indeed, currently the "medical studies" is the most spotted schema in reviews about AI applications. However, this is not specific to AI, it seems to be a general trend. Abd-Alrazaq et al. (2021) conducted a comprehensive overview of the Covid-19 literature in general. They proposed a topic modeling based on the study of almost 29,000 articles. In their proposed six thematic areas, we clearly see a dominance of clinical, epidemiological, and therapeutics topics. As mentioned before, it is just normal that in the midst of a major crisis, responding to immediate threats takes on outsize importance. Nonetheless, as the crisis is extending its impact well beyond the healthcare sphere, it seems of utmost importance to also track other socioeconomic applications. Moreover, as enough data are now available to support "hybrid studies", one should consider using this conceptualization, since it included the medical one but with a larger scope and visibility.

Furthermore, it seems also important to challenge the idea of "one model fits all". One of the valuable lessons offered by the pandemic is that the context matters. The impact of the virus on health and economic outcomes tends to vary heterogeneously across regions and over time (Naudé, 2020a; Naudé, 2020b). Hence, contextual studies based on contextual data are required to guide an adapted and granular use of AI according to the temporal and socioeconomic circumstances.

Finally, this analysis shows an intriguing finding. The datasets used by AI applications surfer generally form small size and the lack of publicly available data. A fact that contrasts the data hungry nature of the most dominating AI methods identified, namely machine learning and deep learning models. This would most likely drive AI research towards more data efficiency and openness.

3. Quo vadis artificial intelligence? Ai in post-covid-19 era

Our umbrella study's results support three main conclusions:

(1) The mobilization of the AI community to address the pandemic issues is unprecedented, the dynamic characterizing the response, is moving rapidly the aim of the literature from solving the "now" to preparing the "beyond". However, the number of works discussing the after-covid is still limited so far. More systematic syntheses are needed in the literature to summarize the current state of research and to set pertinent research agendas for the future.
(2) While AI methods have helped almost every conceivable sector, our findings reveal that the most heavily examined applications by existing review studies come from the fields of healthcare, epidemiology, and public health. The AI applications identified by the reviews reflect the absolute priority given to the medical aspect of the response.
(3) The majority of works employed ML and DNN algorithms, and are found to have more potential, robust, and advanced applications among the other AI components according to the studied reviews.

All these observed dynamic and facts, make it crucial to urgently start portraying and planning for a post-Covid-19 phase. However, while we are heading toward the "New Normal", the outlook is still grim and uncertain. At the time of this writing, the virus is still bringing more unforeseen twists and turns. Hence, we believe that the most important role of AI in the next phase would be to understand the new realities that will emerge beyond the crisis. AI will be a vital tool to identify change patterns in economic, healthcare, and social practices, and to manage new development paradigms.

Certainly, current and future use of AI is driven transformative research in this field. Indeed, it is becoming clear now that the pandemic represents a turning point for AI, where there would be a "before" and an "after". We advocate that, at this point in time, exploring, discussing, and preparing for the "after" AI in the world we will inherit after the pandemic, require proper attention.

Therefore, with the aim of providing some insights into AI new frontiers, we propose in this section a thematic discussion that emphasizes some research pathways which, from our point of view, hold the potential to define the AI landscape in the post-pandemic era. The conducted work of literature synthesis formed the basis for a horizon scanning, that allows us to detect early signs of potentially important AI research developments. The identified research pathways were grouped in seven complementary thematic areas that give a complete picture of developments "on the horizon".

3.1. Data efficient models

Covid-19 has hugely impacted the way we live, work, consume and socialize. As we are witnessing a shift in many habits, priorities, and even values, pre-Covid data, or even data that are produced during the pandemic, will probably not be valid, as they do not account for recent societal and economic changes. For instance, models built for retail businesses relying on massive amounts of historical data to discern patterns from which to make decisions, are now delivering predictions that are no longer valid (Naudé, 2020a; Naudé, 2020b), since businesses no longer have relevant data about new retail consumer behaviors and habits. And it will likely take some time to collect new data that reflect the new realities. However, critical and important decisions will have to continue to be made even with limited data. Hence, in the post-pandemic period, AI models will be required to work even in small data regime. However, current AI leading approaches including ML and DNN are notoriously data-hungry, the larger the dataset available to train them, the more accurate they will be. As a result, the impressive performance and accomplishments of these models depend largely on the use of huge datasets. To properly address this issue, the literature suggests three data-efficient approaches (Adadi, 2021).

First, reducing the dependency of such models upon the amount of samples without impacting their performance means using non-supervised algorithms that are, by nature, more data-efficient. Indeed, when we get into data hungriness issue, we are mostly referring to supervised learning algorithms. Supervised methods need labelled data to build classification and regression models and the performance of these classifiers relies heavily on the size of labelled training data. One straightforward strategy to optimize the need for data would be then the use of unsupervised, semi-supervised or self-supervised methods.

Another data-efficient approach is to create artificially more data, such approach is known as data augmentation (DA). DA encompasses a set of methods that apply transformations on the original training data and synthetically creating new samples (Shorten and Khoshgoftaar, 2019). Basically, it acts as a regularizer in classification problems to reduce the "overfitting" caused by limited training data. During the pandemic, the literature reported significant use of DA for generating synthetic radiological images, especially the use of generative based augmentation schemas (i.e., using GAN).

To fight the data scarcity problem, some research explored the use of prior knowledge in learning new tasks and solving new problems with little data and effort. Depending on how, when and what extent of prior knowledge is used, the research is conducted under different guises, currently the four main ways of reusing knowledge found in the literature are (a) Transfer Learning (Tan et al., 2018) including domain adaptation, fine tuning and pre-trained models, (b) Multi-Task-Learning (Zhang and Yang, 2021), (c) Lifelong Learning (Parisi et al., 2019), and (d) Few shot learning including Meta-Learning (Wang et al., 2020a; Wang et al., 2020b; Wang et al., 2020c). Among the four approaches, transfer learning is probably the one being largely used during the pandemic. Deep transfer learning models were typically used for Covid-19 diagnosis when not enough data are available for training DNN.

Data scarcity is not a new problem, some domains suffer from this issue long before the pandemic outbreak, such as medicine, epidemiology and robotics or any domain studying rare phenomena or aggregating models where the population itself is limited. However, in the light of Covid-19 implications, the scope of these domains is expected to expand. Indeed, many of the included studies highlighted the issue of managing small datasets (Naudé, 2020b; Latif et al., 2020; Shorten et al., 2021; Syeda et al., 2021). For instance, Tayarani (2021) pointed out that the small Covid-19 datasets result in over-fitting problems and that new approaches for dealing with small datasets should be explored. Shorten et al. (2021) explained that the current state of DNN relying on large datasets for improved performance is problematic for a pandemic response situation where quick response is crucial and creating large datasets is extremely challenging. Naudé (2020b) claimed that one of the practical difficulties hindering AI from being impactful against Covid-19 is the limited data. Hence, handling data-efficiency is expected to be as important as handling the performance of AI models. In this sense, unlabeled data, augmentation schemas and prior knowledge are expected to be game-changers for AI to move forward beyond supervised, data-hungry models. The research community is called to bring its attention to these promising concepts and to explore new approaches for dealing with small datasets.

3.2. Sustainable models

The same way pre-covid data may no longer be valid, pre-covid models run the same risk. Indeed, most AI models degrade gradually when the data they were trained on no longer reflect the present state of the world (Lu et al., 2019). For AI, and for ML models to produce valuable results, it's essential to train them using stable data that accurately reflect the underlying reality of the operating regime. Suppose, for example, a model that has been trained with data from 2010 until 2019 to predict bond prices, during which the following fact held true, bonds have an inverse relationship to interest rates. However, in March 2020, stocks and bonds both go down together, something never seen in the training data. Responding swiftly and agilely to this drastic shift involves retraining and redeploying models faster than changes in the operating regime. However, the culture and thus the enabling technologies of handling fast model drift is not yet mature. Currently, for most organizations, AI productization, that is the process of moving a model from the development into production and keeping them updated as operating regimes change, is very challenging and resource-intensive. Especially if the changes are large, rapid and without precedent -like a pandemic. Some of the recent reviews, that have been studied in the umbrella review, have pointed out this issue (Tayarani, 2021; Hussain et al., 2020).

An emerging discipline that tries to address this issue is ModelOps (Hechler et al., 2020). AI model operationalization (ModelOps) is a set of capabilities that focuses on the governance and the full life cycle management of all AI models including models based on ML, knowledge graphs, optimization, natural language techniques and agents. ModelOps uses Auto-AI and DevOps technologies, such as continuous integration and continuous deployment (CI/CD), in addition to continuous training (CT), to regularly update the models while ensuring quality results. It focuses on rapidly and iteratively moving models through the analytics life cycle so they can match the change pace and deliver expected business value. Developing and maturing further this discipline need to be taken heed in the aim of building resilient AI systems.

On the other hand, researchers need to investigate further the reasons that potentially lead to the deterioration of the performance of AI and learning models in changing real-world data (i.e., model drift). Specifically, new and effective mechanisms are needed to detect and address data and concept drift, the two most common causes of model drift. Both drifts involve a statistical change in the data. Concept drift (Lu et al., 2019) refers to the problem of learning in non-stationary distributions over time, the dynamic of target concepts deteriorates the performance of classifiers learned from past instances. While data drift (Barddal et al., 2017) is concerned with learning from input data with changing statistical proprieties (features) leading to model failure as time passes. While drifts have always been an issue for data science, their impact has accelerated aggressively and has reached unprecedented levels due to the Covid-19 pandemic. Hence, the research in this field needs to be renewed taking into consideration the current circumstances. In this sense, recently, a team of researchers at Google has identified a new reason for model's degradation called underspecification (D'Amouret al., 2020), they showed that the small variation and changes during training, when accumulates, can lead to a huge impact on how the models perform in real world. In their paper (D'Amouret al., 2020), they inaugurated the research in this vein by proposing different avenues to address underspecification issue.

3.3. AI democratization

Before the pandemic outbreak, researchers were often cautious about sharing their data and models. However, in a global crisis, data sharing and open models were identified as a key contributor to accelerate the research to contain and eradicate the virus. The lack of global coordination on data and methodology not only has consequences on the management of the health issues, but also worsen the unequal socioeconomic impact of the pandemic, for developing countries in particular. Hence, amid the pandemic, openness has taken human and solidarity dimensions. This spirit has motivated many data-sharing initiatives and open-source algorithms efforts, which have been remarkably reported by the included studies (Pham et al., 2020; Latif et al., 2020; Bansal et al., 2020; Bullock et al., 2020; Abd-Alrazaq et al., 2020; Rasheed et al., 2021; Piccialli et al., 2021). Among these initiatives, we note the Covid-19 Open Research Dataset (CORD-19) (Wang et al., 2020a; Wang et al., 2020b; Wang et al., 2020c, a large and growing collection of publications and preprints on Covid-19 and related historical coronavirus research. WHO's Global Research on Coronavirus Disease Database[2], an openly accessed database gathering the latest international multilingual scientific findings and knowledge on Covid-19. OpenData portal (Brimacombe and Tongan, 2020) developed by the National Center for Advancing Translational Sciences (NCATS) to openly and quickly share Covid-19-related drug repurposing data and experiments for all approved drugs. And the Covid-19 Data Platform[3] launched by the European Commission to facilitate the rapid and open collection and comprehensive data sharing of available research data from different sources for the global research communities. To guide researchers to find the appropriate open-source datasets for their research, many studies provided an exhaustive listing of available open-source Covid-19 datasets (Alamo et al., 2020; Kalkreuth and Kaufmann, 2020; Shuja et al., 2020). On the algorithmic ground, Linda Wang et al. (2020a), Wang et al. (2020b), Wang et al. (2020c) introduced COVID-Net, a deep CNN design tailored for the detection of Covid-19 cases from chest X-ray images that is open source and available to the general public. Javaheri et al (2020) proposed CovidCTNet, an open-source deep learning approach to identify Covid-19 using CT images. EfficientNet is an open source DNN designed by Google that has been extended by Roy et al. (2020) to classify and locate Covid-19 markers in Lung Ultrasound images, and the list goes on.

Visibly, the global pandemic has prompted the openness and sharing mindset, a practice that was not very often adopted in AI field before. Yet it is not clear if this trend will persist in the future or it will remain just a temporary impact of the pandemic. On one hand, an open AI contributes to democratize technology and reduce the associate divide. Indeed, shared knowledge extracted from public datasets using open AI technologies can help in bridging the digital divide and technological inequality in a post-covid world pushed into an accelerated digitalization. On the other hand, however, a post-covid era of openness comes with concerns around privacy, ethics and legal requirements. Among the three concerns, privacy is already a controversial topic, the "privacy issue vs public health imperatives dilemma" is probably one of the most debated subjects during the Covid-19 pandemic (Naudé, 2020a; Pham et al., 2020). Data openly accessed could be sensitive in nature, and learning models on these data may expose highly sensitive information about individuals violating their privacy. Looking forward to wide-scale adoption of sharing and openness mindset requires therefore promoting innovation and advancing research in privacy-preserving technologies. In this regard, a promising area of research that is expected to flourish in the post-covid era, mainly due to its potential to help in restoring privacy, is federated learning (FL)(Truex et al., 2020). Also known as privacy preserving machine learning, this novel strategy of learning allows data holders to collaborate throughout the learning process rather than relying on a trusted third party to hold (Truex et al., 2020). Basically, it enables multiple entities who do not trust each other, to collaborate in training an ML model on their combined dataset, without explicitly having to share the data. FL is emerging as a prospective solution for distributed collaborative learning in less open trust boundaries. However, FL in its vanilla form is not sufficient for privacy-guarantee, the model can be exploited in privacy attacks. Hence, research must be activated towards more robust, secure, and privacy-preserving versions of FL (Truex et al., 2020; Nguyen and Nguyen, 2020).

3.4. Autonomous everything

It needs no arguments that the ongoing pandemic has pushed automation into new areas. The longstanding trend toward manufacturing automation has understandably been accelerated by the pandemic. Nonetheless, in addition to industries that have always been subject to automation, automation has also strongly penetrated new sectors that traditionally experienced relatively low productivity growth such as healthcare and education. Some of the included studies have noted the increasing penetration of automation in the healthcare systems during the pandemic (Shen et al., 2020; Wang and Wang, 2021; Piccialli et al., 2021). As discussed by Shen et al. (2020) in their study, traditional and direct human labor has faced enormous challenges due to the high contagiousness and infection fatality rate of the virus, which lead to a remarkable increase in the robotic systems' acceptability. Therefore, as industries and vital sectors progressively embrace advanced automation throughout the value chains, it is only a matter of time before autonomous systems will be everywhere.

Pervasive automation is likely to be further developed in the after Covid-19 as an entirely new set of demands, previously undiscovered, are now critical. Indeed, as business adaptability and resiliency become a key competitive advantage, automation will continue to be on the rise, in its evolution from lower-level, more basic forms of automation such as basic physical robotics, to higher-level forms such as Robotic Process Automation (RPA) and hyperautomation (Aalst et al., 2018). Automation is also evolving in scope, we are witnessing the move from task-based automation, passing by process-based automation, to functional automation across multiple processes and even moving towards automation at the business ecosystem level.

Accordingly, research related to enabling technologies for pervasive automation will also grow. Future studies are expected to make robots more autonomous, flexible, and cooperative (Almeida et al., 2020). Robots will be designed more to interact with people. Hence, new technologies like human-robot interaction and collaboration (HRI) (Feil-Seifer et al., 2021) are expected to play more important roles in the future of automation. Probably, more human-centered HRI approach should be proposed in order to build advanced social robots with artificial empathy. Vision is central to these autonomous systems, thus, robot vision with advanced computer vision capabilities will be further developed to enable more objective and faster decision-making for autonomous agents. After their success story in handling communication and public information amid- the crisis, bots will surely have new and innovative implementations enabled by DNN and NLP. And as foreseen by Gartner[4], hyperauomation will likely become a strategic technology driven by (i) digital twin (Tao et al., 2019) for more adapted solutions based on virtual simulation of physical assets, and (ii) RPA to emulate the human behavior in executing businesses process.

3.5. Generative everything

Similarly to the trend of autonomous everything, we should also expect a "generative everything" influx. As emphasized by

[2] https://search.bvsalud.org/global-literature-on-novel-coronavirus-2019-ncov/

[3] https://www.covid19dataportal.org/

[4] https://www.gartner.com/smarterwithgartner/gartner-top-10-strategic-technology-trends-for-2020/

the findings of the studied reviews, in 2020, we witnessed significant progress in computer vision and complex DNN architectures (Ulhaq et al., 2020; Shorten et al., 2021). As a natural consequence, AI with creative capabilities emerged. Generative AI (Houde et al., 2020) refers to algorithms that allow composing artificially original artifacts in form of text, audio, and images to a sufficiently high standard that it is difficult to distinguish between synthetic and non-synthetic content. The advance in this field was largely made possible due to (i) GAN, a type of neural network that is trained using two models set up in a contest or a game. (ii) advances in computer vision, notably, object recognition, activity recognition, semantic segmentation, and human pose estimation. And (iii) vision and language reasoning.

As depicted before, generative AI is a relevant tool for DA, but it can also find application in many other scenarios. In medical settings, it can be used to create medical images that depict the future development of a disease. In drug discovery, the generative models can be used for generating molecular structures for medicines. In the marketing sector, it can enable innovative experiences for customers such as "try-on" articles virtually. In the entertainment industry, the video game industry can benefit hugely from generative AI through automatic generation of 3D models and automatic generation of facial images of characters. In robotics, creative robots capable for example of navigating through an imaginary environment without actually running into real obstacles could be designed using generative models. Now, with the shift caused by the pandemic in habits, behaviors, and business strategies, generative models are expected to span more and more in all areas of life.

However, there is a kind of research loop in this field hindering its overall advancement. First, research efforts were made toward sophisticating the generated artifacts. As a result, advances in artifact synthesis have created new opportunities as well as threats. Indeed, recently generative AI has gained a partly negative reputation because of deep fakes (malicious uses of generative models) (Houde et al., 2020). And this has caused researchers to increasingly invest in DeepFake detection[5] and the development of techniques to counteract AI-generated misinformation. Relieving generative AI from such investment and research efforts probably requires tackling at a higher level the issue of accountable and responsible design and use of generative models. We believe that individual efforts of different AI communities to address their respective concerns associated with the use of AI should be joined and studied as a research area with its own identity, namely Ethical AI.

3.6. Ethical AI

In part as a consequence of the other research directions discussed in this section, the pressure will mount to build ethical and trustworthy AI. Indeed, democratizing AI and data entails equity, fairness, ethics, and privacy considerations. Advanced automation raises concerns about the responsible design, control, and use of autonomous robots especially socially interactive ones. And AI-based synthetic media also poses ethical challenges since it can be maliciously used and causes social harms. Thus, it is only natural that ethical AI will emerge alongside the emergence of the discussed trends. In fact, before the pandemic, there were already several distinct legal and ethical challenges posed by the use of AI. However, many of the challenges were considered futuristic. Now, in many ways, Covid-19 is pulling forward the future and ethical AI is becoming a subject to scrutiny. Precisely speaking, as concluded in the umbrella review, the pandemic was an opportunity for AI to unleash its full power. Because of the urgent nature of the crisis, outsized priority was given to medical response above all else. Resulting in a large deployment of AI solutions with a scale and a speed that probably may not otherwise have been possible. Which, in return, has brought to the fore ethics concerns, especially regarding surveillance and control applications. The ethical issue has been outlined in many of the included studies (Naudé, 2020a; Nguyen et al., 2020; Latif et al., 2020; Bullock et al., 2020; Shorten et al., 2021; Piccialli et al., 2021). For instance, Bullock et al. (2020) believe that AI application should undergo an assessment to ensure that it complies with ethical principles and respects human rights. Piccialli et al. (2021) argued that despite their undeniable potential advantages, frameworks for medical diagnosis based on AI may pose problems in comprehension and transparency concerning prediction. Naudé (2020a) cautioned that the flexibility in gathering and analyzing personal data imposed under the pandemic circumstances may cause the loss of trust and confidence of the public. Hence, restoring privacy, trust and confidence is expected to appear at the top of the list of research goals in the next phase.

There are three complementary guiding forces for ethical AI (i) law, (ii) organizational guidelines, and (iii) technology. On the legal front, in the last few years, numerous regulations were set up to govern AI use, the EU's General Data Protection Regulation (GDPR)[6] and the California Consumer Privacy Act (CCPA)[7] are examples of regulations pushing toward data privacy and explanation right. However, to fully ensure regulatory compliance and safety of AI systems, robust procedures and personalized AI-related ethics guidelines are needed. In this vein, at the organizational level, considerable work has already been done to develop high-level principles (Lo Piano, 2020). Nonetheless, many critics of such principles let much room for improvement. Mittelstadt (2019) believes that existing principles still vague, high-level, and lack action guidance. He also noted that AI's ethical guidelines have seemingly converged on the four classic principles of medical ethics, regardless of the significant differences between medicine and AI development. Moreover, existing principles do not study cases where principles come into conflict with one another (Tzachor et al., 2020). For example, how to manage situations where the principle of "beneficence", that is the potential of AI to save lives, contrasts other important values such as privacy or fairness. On the technical ground, Responsible AI operationalized through Explainable AI is seen as a promising mechanism to increase algorithmic fairness, transparency and accountability. As its name suggests, responsible AI is an approach that aims to consider the ethical, moral, and social consequences during the development and deployment of AI systems (Dignum, 2019). Explainable AI is a field that aims to create a suite of techniques that produce responsible models by making them human-interpretable while maintaining their high predictive performance (Adadi and Berrada, 2018). Explainable AI is practically useful for DNN. Indeed, in their current incarnation, deep models suffer from the lack of interpretability, as it is difficult to identify what process has been used to determine the output. This restricts AI models acceptance and use, since entrusting important decisions to a system that cannot explain itself presents obvious dangers. The interpretability of "black box" neural networks has been a major focus of discussion in the last few years. However, it remains open how to compare (evaluate) between different produced explanations, and thus how we would construe the "best algorithmic explanation". It still also underexplored how to interpret the outputs of non-machine learning methods (e.g., explainable robots and agents, explainable AI planning...). Considering what explainable AI has

5 https://www.kaggle.com/c/deepfake-detection-challenge

6 https://gdpr.eu/

7 https://oag.ca.gov/privacy/ccpa

achieved so far and what it is expected to achieve, it is fair to say that this field is just in its infancy, but we believe that the post-covid period will be a golden time for its rise.

3.7. Precision AI

A wide range of AI methods has been employed to deal with every aspect of the pandemic. When existing methods did not reach the expected results, researchers tended to opt for a composite approach that aggregates multiple AI systems, namely ensemble methods (Dong et al., 2020). To gain even more efficiency and performance, some proposals in the literature suggested building entirely novel models designed specifically for the pandemic. This approach was particularly common practice for ML and DNN. The review of Tayarani (2021) gives many illustrative examples of new algorithms proposed during the pandemic. Scholars justified their choice by the fact that generic architectures do not take into account the peculiarities and the unique characteristics of the pandemic issues, especially ones involving diagnosis and epidemiological tasks. Thus, it was necessary to design a specific architecture for these specific tasks. As a result, during the pandemic, DNN architectures proliferated into new forms such as ReCoNet, COVNet, and others (Tayarani, 2021). The design of personalized architectures is not new in DNN, over the past ten years, various modifications driven by various reasons have been achieved in the deep architecture (Alzubaidi et al., 2021). If we take CNN as an example, CNNs began with the appearance of LeNet dedicated to handwritten digit recognition tasks, which cannot be scaled to all image classes. Afterward, AlexNet was designed for the fields of image recognition and classification, then ResNet was introduced as a novel architecture robust against the problem of overfitting. Very recently, HRNet was designed specifically for position-sensitive vision tasks, such as semantic segmentation, object detection, and human pose estimation. Each of the mentioned architectures has its own identity, its own spectrum of research, and its unique problem from which it has emerged. Moreover, the "good" performance by one of these models in particular settings do not necessarily translate to other applications. This pattern of evolution based on continuous personalized mutation can lead us to an analog concept to "precision medicine" (Hodson, 2016), in which diagnostic and therapeutic strategies are individually and precisely tailored to each patient's requirements and variability. If this logic is followed, we can imagine a "precision AI" (or at least precision DNN) tailored and tuned to each problem' requirements and variability. In contrast to the theory that proposes to unify intelligence into a single general-purpose model or a "master algorithm" that can work in any domain (Domingos, 2015), precision AI presents a vision of a personalized and flexible intelligence much like the diversity and complexity of how the brain is operating. The current AI methods and how they are evolving are already implementing this concept at its high level, for example AI security is gaining the notoriety of being a standalone field. But given the way AI has specialized during the pandemic, we can expect that in the future the use and usefulness of generic methods and architectures will progressively decline to become just theoretical. AI next generation will rely less on these generic "one-size-fits-all" models and more on specialized and personalized models.

AI methods alone cannot achieve precision intelligence. For example, a successful shift to digital working during the crisis was largely made possible by the use of an enhanced form of AI, in which AI methods were combined with other technologies. Typically, a "precision" solution for remote working integrated ML coupled to IoT and big data to ensure remote operations. Edge commuting and 5G were paired to ensure robust and controlled remote infrastructure. While cyber-safe working was ensured by AI security combined with other risk mitigation technologies such as blockchain. The Covid-19 pandemic has directed research towards a crisis-focused approach, which means that introduced solutions are more problem/application ad hoc and less mono-technology. This research approach encourages exploring new opportunities and innovative solutions lying at the intersection of AI with other technologies. Hence, in the future, it will become probably more obvious to use a composite intelligent technology with a blurring of the boundaries between combined technologies. As will become crucial to combine under one map the entire multidisciplinary scholarship related to the disruptive technology landscape, in order to enable such powerful synergy.

Overall, the forward-looking exercise implies that Covid-19 is pushing the research on AI towards avenues that have implications for global development as they highlight important aspects such as trust, ethics, equality, and sustainability. Beyond the pandemic, to be effective, a learner should optimize on the size of data it requires. It should be able to track changes and quickly adapt to them. Furthermore, in the future, intelligent systems would probably be more open and democratized, which will lead to reinforcing the already underway debate on privacy and ethical issues. Thus, new privacy-enhancing technologies and explainable models will emerge. Finally, the after-pandemic phase will arguably see more ad-hoc solutions focusing on a personalized form of AI.

4. Limitations and future scope

4.1. Limitations

The findings in this manuscript are subject to some limitations.

First of all, we only considered papers in the English language and for which full text is available, which may introduce some bias in our analysis.

Second, since our objective is to synthesize the whole picture of the AI contribution against the pandemic, we did not select reviews focusing solely on one area of AI applications. Thus, there is a possibility that some of the excluded reviews may have some useful insights regarding a specific AI application.

Furthermore, an inherent limitation of the umbrella review approach is that the review is limited by the amount, quality, and comprehensiveness of available information in the primary review studies. Pre-existing reviews may not cover all of the possible AI applications or all AI methods. For example, some algorithms may be relevant, but if they were not enough investigated in the empirical studies they may not be included in the surveyed reviews.

Finally, as the COVID-19 pandemic is still ongoing, we expect the research trends to continuously change. However, given the number and diversity of the databases used for article retrieval and the selection process adopted, we are confident that a large part of the targeted literature was covered and that the results illustrate well the current state of research.

4.2. Future scope

We believe there are a number of future scopes for further research that become evident when approaching the topic from a synthesis and future-projection perspective as we have done in this review.

The first direction for future research is in conducting more synthesis reviews such as *meta*-analysis studies to capitalize on the knowledge and know-how built up during the Covid-19 and develop a model of an AI based crisis-response plan to fight similar pandemics and crises. Furthermore, it is also important to run more foresight studies in order to provide diverse points of view of the post-pandemic era and stimulate debate on the issues involved.

The second direction is to invest more in contextual studies. AI's role amid and post-pandemic is likely to be dissimilar between countries and over time, so there remains a need for further research on the issue from a contextual perspective to guide an adapted and personalized use of AI according to the temporal and socioeconomic characteristics.

Finally, the third direction is in studying and reviewing other technologies that played a strong role in managing the pandemic (Javaid et al., 2020a; Javaid et al., 2020b; Chamola et al., 2020), and which hold the potential to define the post-Covid-19 era along with AI. These include, but are not limited to, IoT (Pratap Singh et al., 2020; Singh et al., 2020b), Blockchain (Marbouh et al. 2020), Edge Computing (Sufian et al., 2020), Virtual Reality and Augmented Reality (Singh et al., 2020a), Quantum Computing (Saunders, 2020), 5G (Chamola et al., 2020), and Cyber Security (Lallie et al., 2021).

5. Conclusion

In this paper, we provided a bird's eye view of the body of research reviewing AI application in the Covid-19 pandemic. The umbrella review, drawing from the findings of existing reviews, offered a clear overview of how research community reacted, what characterized its contributions, and how research efforts developed over time. It also systematized the variant conceptualizations adopted to classify AI applications in one unified *meta*-taxonomy, and highlighted applications for which there is stronger evidence for the AI effectiveness, as well as those for which there is limited evidence-base. Broad insights from this synthesis exercise show that (i) the most prevalent AI applications are related to the health response. (ii) DNN models are dominating the landscape of AI solutions devoted to Covid-19. (iii) Reviews with synthesis aim and anticipation vision are scarce in the explored literature.

The knowledge gathered from the umbrella review was used to conduct a foresight exercise for the post-pandemic period, the results predicted that the next AI generation will exhibit the properties of efficiency, sustainability, openness, autonomy, creativity, responsibility, and precision/personalization.

Being the first of its type, this examination of review studies may be useful for research scholars, especially as a comprehensive reference of AI-related review studies conducted during the pandemic peak. Future researchers that would be interested in this phase, could refer to this study to gain a quick and holistic view of the body of research that characterized this period.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Included reviews

N°	Authors	Title	Review type
1	Naudé (2020)	Artificial Intelligence against COVID-19: An Early Review	Literature review
2	Vaishya et al. (2020)	Artificial Intelligence (AI) applications for COVID-19 pandemic	Rapid Review
3	Naudé (2020)	Artificial intelligence vs COVID 19: limitations, constraints and pitfalls	Literature review
4	Bragazzi et al. (2020)	How Big Data and Artificial Intelligence Can Help Better Manage the COVID-19 Pandemic	Literature review
5	Kumar et al. (2020)	A review of modern technologies for tackling COVID-19 pandemic	Rapid Review
6	Alabool et al. (2020)	Artificial intelligence techniques for Containment COVID-19 Pandemic: A Systematic Review	Systematic Review
7	Ahuja et al. (2020)	Artificial intelligence and COVID-19: A multidisciplinary approach	Literature survey
8	Hossain et al. (2020)	Applications of artificial intelligence technologies in COVID-19 research: A bibliometric study	Bibliometric study
9	Fong et al. (2020)	AI-Enabled Technologies that Fight the Coronavirus Outbreak	Literature review
10	Chen et al. (2020)	A Survey on Applications of Artificial Intelligence in Fighting Against COVID-19	Literature survey
11	Hussain et al. (2020)	AI Techniques for COVID-19	Literature survey
12	Pham et al. (2020)	Artificial Intelligence (AI) and Big Data for Coronavirus (COVID-19) Pandemic: A Survey on the State-of-the-Arts	Literature survey
13	Nguyen and Nguyen (2020)	Artificial Intelligence in the Battle against Coronavirus (COVID-19): A Survey and Future Research Directions	Literature survey
14	Latif et al. (2020)	Leveraging Data Science to Combat COVID-19: A Comprehensive Review	Systematic Review
15	Bansal et al. (2020)	Utility of Artificial Intelligence Amidst the COVID 19 Pandemic: A Review	Literature review
16	Islam et al. (2020)	A Survey on the Use of AI and ML for Fighting the COVID-19 Pandemic	Systematic Review
17	Ulhaq et al. (2020)	COVID-19 Control by Computer Vision Approaches: A Survey	Literature survey

(*continued on next page*)

Appendix (*continued*)

N°	Authors	Title	Review type
18	Enughwure and Febaide (2020)	Applications of Artificial Intelligence in Combating Covid-19: A Systematic Review	Systematic Review
19	Naseem et al. (2020)	Exploring the Potential of Artificial Intelligence and Machine Learning to Combat COVID-19 and Existing Opportunities for LMIC: A Scoping Review	Scoping Review
20	Lalmuanawma et al. (2020)	Applications of Machine Learning and Artificial Intelligence for Covid-19 (SARS-CoV-2) pandemic: A review	Systematic Review
21	Chen and See (2020)	Artificial Intelligence for COVID-19: Rapid Review	Rapid Review
22	Raza (2020)	Artificial Intelligence Against COVID-19: A Meta-analysis of Current Research	Meta-analysis
23	Tseng et al. (2020)	Computational Intelligence Techniques for Combating COVID-19: A Survey	Literature survey
24	Bullock et al. (2020)	Mapping the Landscape of Artificial Intelligence Applications against COVID-19	Literature review
25	Chiroma et al. (2020)	Early survey with bibliometric analysis on machine learning approaches in controlling coronavirus	Bibliometric study
26	Chang (2020)	Artificial intelligence and COVID-19: Present state and future vision	Literature survey
27	Abd-Alrazaq et al. (2020)	Artificial Intelligence in the Fight Against COVID-19: Scoping Review	Scoping Review
28	Shen et al. (2020)	Robots Under COVID-19 Pandemic: A Comprehensive Survey	Literature survey
29	Nadeem et al. (2020)	A Survey of Artificial Intelligence and Internet of Things (IoT) based approaches against Covid-19	Literature survey
30	Chawki (2021)	Artificial Intelligence (AI) Joins the Fight Against COVID-19	Literature review
31	(Syeda et al., 2021)	Role of Machine Learning Techniques to Tackle the COVID-19 Crisis: Systematic Review	Systematic Review
32	Shorten et al. (2021)	Deep Learning applications for COVID 19	Literature survey

Appendix (*continued*)

N°	Authors	Title	Review type
33	Kamalov et al. (2021)	Machine Learning Applications for Covid-19: A State-Of-The-Art Review	Literature review
34	Tayarani (2021)	Applications of Artificial Intelligence in Battling Against Covid-19: A Literature Review	Literature review
35	Wang and Wang (2021)	A literature survey of the robotic technologies during the COVID-19 pandemic	Systematic Review
36	Nirmala and More (2020)	Role of Artificial Intelligence in fighting against COVID −19	Literature survey
37	Senthilraja (2021)	Application of Artificial Intelligence to Address Issues Related to the COVID-19 Virus	Literature review
38	Ahuja and Nair (2021)	Artificial Intelligence and technology in COVID Era: A narrative review	Literature review
39	Khemasuwan and Colt (2021)	Applications and challenges of AI-based algorithms in the COVID-19 pandemic	Literature review
40	Rasheed et al. (2021)	COVID 19 in the Age of Artificial Intelligence: A Comprehensive Review	Literature review
41	Safdari et al. (2021)	Using data mining techniques to fight and control epidemics: A scoping review	Scoping review
42	Arora et al. (2020)	The role of artificial intelligence in tackling COVID-19	Literature survey
43	Zhao et al. (2021)	Applications of Robotics, Artificial Intelligence, and Digital Technologies During COVID-19: A Review	Systematic Review
44	Gunasekeran et al. (2021)	Applications of digital health for public health responses to COVID-19: a systematic scoping review of artificial intelligence, telehealth and related technologies	Scoping Review
45	Piccialli et al. (2021)	The Role of Artificial Intelligence in Fighting the COVID-19 Pandemic	Literature review

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