

Questioning the impact of AI and interdisciplinarity in science: Lessons from COVID-19

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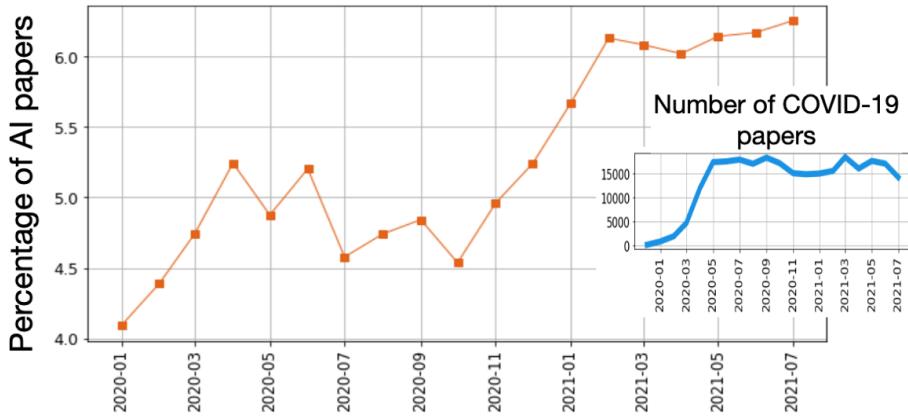
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Abstract. Artificial intelligence (AI) has emerged as one of the most promising technologies to support COVID-19 research, with interdisciplinary collaborations between medical professionals and AI specialists being actively encouraged since the early stages of the pandemic. Yet, our analysis of more than 10,000 papers at the intersection of COVID-19 and AI suggest that these collaborations have largely resulted in science of low visibility and impact. We show that scientific impact was not determined by the overall interdisciplinarity of author teams, but rather by the diversity of knowledge they actually harnessed in their research. Our results provide insights into the ways in which team and knowledge structure may influence the successful integration of new computational technologies in the sciences.

Interdisciplinarity has become the buzzword in science policy. And with very good reason. Disciplines have for decades – in some cases centuries – facilitated scientific progress by providing scholars with the scaffolding of a coherent paradigm and with the possibility of standing on the shoulders of their predecessors. However, disciplinary boundaries have often proved to be a stumbling block to development, as growing specialization makes it ever harder (though ever more necessary) for scientists to venture into unexplored territories and combine practical and intellectual tools originating from different traditions (Jones, 2009). These entrenched boundaries are especially problematic when we find ourselves facing unprecedented research challenges that require fresh thinking and unrestrained experimentation.

Just such a situation presented itself recently with the outbreak of the COVID-19 pandemic. The urgency and gravity of the situation prompted researchers in epidemiology and medical science not only to mobilize all the resources available within their disciplines, but to look beyond them for new ideas and external collaborations. And among them, the alliance with artificial intelligence (AI) emerged as one of the most promising (Fig. 1).

Figure 1. COVID-19 publications with AI content



Notes: Fraction of COVID-19 papers containing AI. Inset: Total number of COVID-19 papers containing AI. After an initial period of exponential growth, scientific production related to the COVID-19 virus stabilized in May 2020. At the same time, AI research dedicated to COVID-19 virus remained relatively marginal until summer 2020 when it began to record constant linear growth, so that by July 2021 it accounted for nearly 7% of total COVID-19 scientific production. *Source:* Own elaboration on *CORD-19* data.

Although AI is nothing new, the field has recently been revived by the burgeoning power of computational technologies and the growing availability of data on social and natural phenomena. This has led to the development of new machine learning approaches, which are yielding remarkable results within and beyond data science (Cardon et al., 2018; Frank et al., 2019). The scientific enterprise is no exception to this trend. Some recent studies have shown that AI techniques are indeed changing the “way of doing science,” from agenda setting and hypothesis formulation to experimentation, knowledge sharing, and public involvement, with a far from negligible impact on scientific discovery (Agrawal et al., 2018; Cockburn et al., 2018; Furman and Teodoridis, 2020; Bianchini et al., 2022).

The coronavirus pandemic hit at the peak of this cycle of AI hype and, unsurprisingly, many scholars quickly embraced ideas of adopting AI techniques to tackle the many challenges presented by COVID-19 (DeGrave et al., 2021; Khan et al., 2021; Roberts et al., 2021). Opportunities for collaborative funding have emerged globally to bring various scientific communities together, and researchers from different backgrounds have come together to try to harness the potential of AI in COVID-19 research (Ahuja et al., 2020; Luengo-Oroz et al., 2020). Yet, while some collaborations have made substantial contributions to the fight against the pandemic, others never got beyond the blueprint stage. What can explain these contrasting outcomes?

Interdisciplinary research: Pros and Cons. Previous research shows that (large) interdisciplinary teams produce more cited research and high-impact papers (Wuchty et al., 2007; Fortunato et al., 2018), and that diversity – not only epistemic, but also institutional and ethnic – is beneficial for producing novel, valuable ideas (Taylor and Greve, 2006). Teams comprising researchers with different backgrounds, methodological

approaches, and experience have access to a broader pool of knowledge, which allows them to produce more creative outputs than those produced by traditional, non-collaborative science (Stephan, 2012; Uzzi et al., 2013; Gargiulo et al., 2022). Collaborative projects also serve to boost visibility by exposing scientific findings to a wider and more diverse readership (Leahy, 2016). How does this relate to COVID-19 research? Well, it suggests that collaborations between AI experts and clinicians may have mainly resulted in successful research outcomes, as domain specialists could provide their “on-the-ground” knowledge to identify promising areas for investigation related to the virus and related problems, while technology experts could apply the latest methods. A winning strategy, in short.

However, team diversity can also increase the chances of failure in collaborative research. Teams that are too large and heterogeneous often suffer from lower consensus-building, cognitive diversity, higher coordination costs, and emotional conflict. Thus, as diversity increases, it becomes more difficult to convert specialized expertise into scientific outputs (Lee et al., 2015). Some studies show that a team’s ability to perform well depends more on how the team interacts than on the characteristics of its members (Woolley et al., 2010), and that most successful collaborations seem to be achieved through efforts that, while interdisciplinary, span relatively close fields (Yegros et al., 2015). Therefore, it is possible that conflicts could have arisen in collaborations between AI and COVID-19 experts due to differences in their areas of expertise, and this could have resulted in less impactful and visible scientific outcomes compared to teams consisting of only AI or clinical specialists.

The ultimate impact of interdisciplinarity remains an empirical question, one that we address in this paper. Here, based on a sizeable corpus of scientific publications at the intersection of COVID-19 and AI (~10,000 papers retrieved from the COVID-19 Open Research Dataset, *CORD-19* – version 2021-08-09 – and supplemented by other metadata from *Altmetric*, *OpenAlex*, and *Semantic Scholar*), we study which forms of interdisciplinarity served as the main drivers of scientific impact.

In the remainder, we first describe the metrics of interdisciplinarity that we devised for our study, and then link these metrics to three indicators of scientific “success”, namely the number of citations, online visibility, and outreach to other disciplines.

Measuring interdisciplinarity. Each document, i , in our data is characterized by a set of authors (\mathcal{A}_i), a set of references and citations ($\mathcal{R}_i, \mathcal{C}_i$), a set of AI keywords, if any, (\mathcal{W}_i), the journal in which the paper is published (J_i), and an altmetric score (\mathcal{M}_i). At the same time, for each author, a , present in our corpus we identified his/her list of papers (\mathcal{P}_a) and the list of his/her three most recent papers (\mathcal{P}_a^3).

Based on the co-occurrence of journals, in all the papers’ reference lists, we employed a measure based on pairwise mutual information, to identify a distance matrix, D , among all the journals appearing in the dataset (if two journals are cited together several times their distance is considered small).

With this information, we defined two types of interdisciplinary metrics to evaluate the disciplinary positioning of each AI-COVID-19 paper: the first is related to team composition (measuring the difference in

the scientific disciplinary background of the authors contributing to the paper); the second is related to the knowledge mobilized in the paper, in terms of reference heterogeneity.

For each dimension (team and knowledge), we develop a further distinction between metrics concerning AI (μ_{AI}^{team} and μ_{AI}^{kn}) and those concerning their more general interdisciplinary nature (μ_{GEN}^{team} and μ_{GEN}^{kn}), providing us with four different metrics:

- *AI team metric* is the fraction of previous AI publications for each author, averaged over the entire team:

$$\mu_{AI}^{team}(i) = \frac{1}{\#\mathcal{A}_i} \sum_{a \in \mathcal{A}_i} \frac{\#\{j \in \mathcal{P}_a \mid \mathcal{W}(j) \neq \{\}\}}{\#\mathcal{P}_a}$$

- *AI knowledge metric* is the fraction of cited references related to AI:

$$\mu_{AI}^{kn}(i) = \frac{\#\{j \in \mathcal{R}_i \mid \mathcal{W}(j) \neq \{\}\}}{\#\mathcal{R}_i}$$

- *General team metric* is the average disciplinary dispersion (in term of journal distances) of team authors:

$$\mu_{GEN}^{team}(i) = \frac{1}{\#\mathcal{A}_i} \sum_{a \in \mathcal{A}_i} \left(\frac{1}{3} \sum_{k \neq l \in \mathcal{P}_a^3} \mathbf{D}_{\mathcal{J}(k) \mathcal{J}(l)} \right)$$

- *General knowledge metric* is the average distance among all the journals cited in the references:

$$\mu_{GEN}^{kn}(i) = \frac{1}{\#(\mathcal{R}_i \times \mathcal{R}_i)} \sum_{(u,v) \in (\mathcal{R}_i \times \mathcal{R}_i)} \mathbf{D}_{\mathcal{J}(u) \mathcal{J}(v)}$$

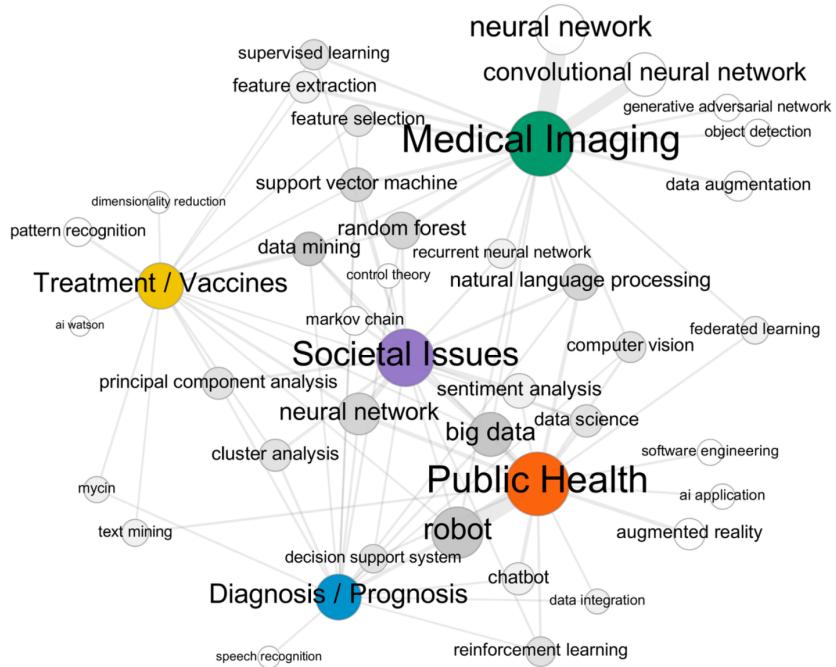
To be clear, the first two metrics, μ_{AI}^{team} and μ_{AI}^{kn} , measure the share of AI in the author teams and knowledge mobilized by the publications in our corpus, respectively. The remaining two, μ_{GEN}^{team} and μ_{GEN}^{kn} , measure levels of general interdisciplinarity in the teams and knowledge, respectively.

For all the papers, we define three different indicators of ‘success’, namely: the *number of citations*, $\mathcal{N}(i)$, the *altmetric score*, $\mathcal{M}(i)$, and the *interdisciplinary spread* – i.e., how a paper is cited in a diverse set of disciplines – defined as:

$$\mathcal{J}(i) = \frac{1}{\#(\mathcal{C}_i \times \mathcal{C}_i)} \sum_{(u,v) \in (\mathcal{C}_i \times \mathcal{C}_i)} \mathbf{D}_{\mathcal{J}(u) \mathcal{J}(v)}$$

By topic modelling on abstracts of the papers in our corpus, we obtained five distinct application areas, which we label as follows: (i) *Societal Issues* (including epidemiology and infodemics); (ii) *Medical Imaging*; (iii) *Diagnosis and Prognosis*; (iv) *Treatments and Vaccines*; and (v) *Public Health*, with the most frequent uses of AI being found in medical imaging, followed by public health and, to a lesser extent, societal issues (Fig. 2).

Figure 2. AI application areas for COVID-19 research



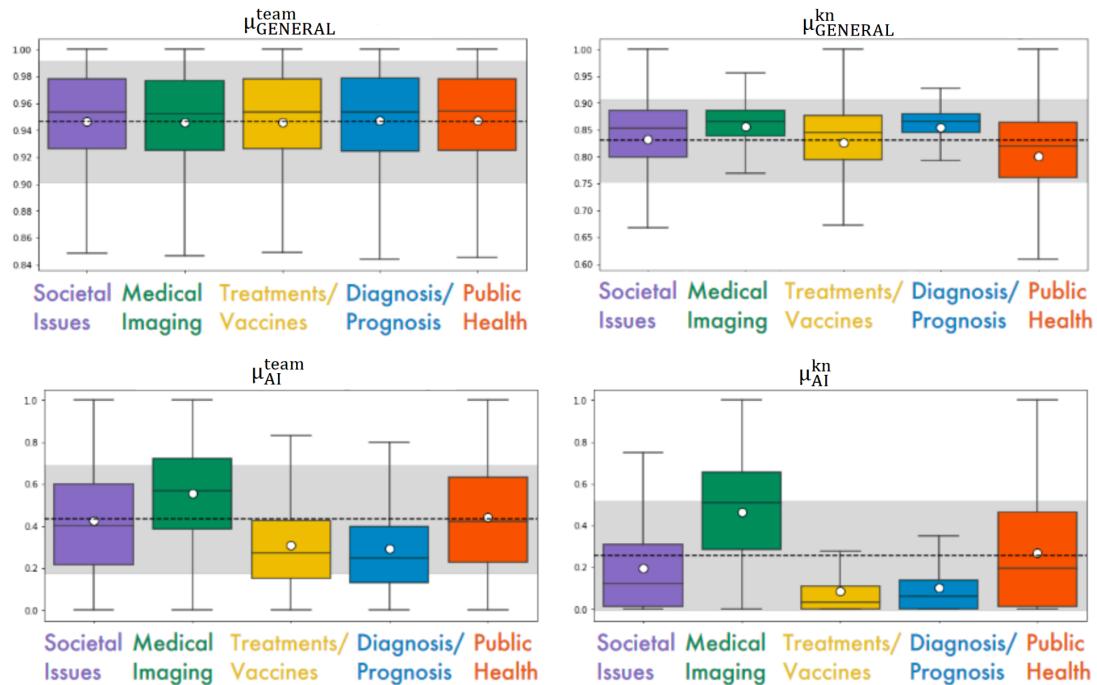
Notes: Co-occurrence of AI keywords (gray nodes) and COVID-19 topics (colored nodes). Edges are weighted by the number of articles that use each keyword in each topic. Nodes are sized according to their popularity (number of articles). Keywords are colored according to their degree, the number of topics in which each keyword is used (white keywords are specific to one topic, dark gray keywords are used in multiple topics).

A closer reading of the terms characterizing each topic suggests that AI has found a multitude of applications (Bullock et al., 2020; Naudé, 2020; Yang et al., 2020; Piccialli et al., 2021). In the case of societal issues, AI seems to have been used mainly for predicting the spread of disease over time and space, modeling public policy interventions (e.g., social distancing) and risk assessment, and fighting misinformation and disinformation on social media. In the case of medical imaging, what we essentially see is the deployment of deep learning models (e.g., CNN) to detect signs of COVID-19 from X-ray images and computed tomography (CT) scans. Another area of application, particularly of machine learning and deep learning, is the

identification of possible treatments and vaccines, as well as the re-purposing of existing drugs. Finally, AI appears to support the management of the public health system, with robotics providing assistance in the delivery of healthcare tasks.

Each application area may have required specific skills and know-how from researchers with diverse backgrounds and experience with AI technology, and not least, the (re)combination of different types of knowledge. Unsurprisingly, our corpus reveals a high level of general interdisciplinarity both in the teams and in the knowledge mobilized by the publications across all research topics – with a slightly higher knowledge heterogeneity in medical imaging and diagnosis and prognosis (Fig. 3 top). In the case of AI, we observe very different scenarios at the topic level. Indeed, the share of teams with more AI experts is markedly higher in medical imaging and public health research, whereas teams working on vaccines, treatments, and prognosis seem to rely very little on AI knowledge (Fig. 3 bottom).

Figure 3. Interdisciplinarity metrics in the different axes of COVID-19 research



Notes: general (top) and AI-related interdisciplinarity (bottom). The dotted line and shaded area represent the mean and standard deviation, respectively.

What determines ‘success’. We modeled the various impact measures – i.e., the number of citations received by the publication, the Altmetric attention score, and the interdisciplinary spread – as a function of four interdisciplinarity metrics discussed earlier – $\mu_{\text{AI}}^{\text{team}}$, μ_{AI}^{kn} , $\mu_{\text{GEN}}^{\text{team}}$, and μ_{GEN}^{kn} – and a set of control variables, namely: *AI Collaborator* (=1 if the team includes at least one AI researcher), *Top AI Collaborator* (=1 if the team includes an AI researcher with past number of citations in the top 10° percentile of the citation

distribution); *Academic Age* (average academic age of team members, in logs); *Past Impact* (average H-Index of team members based on past publications, in logs); *Nb. Countries* (number of participating countries within a team, in logs); and *Nb. References* (number of cited references, in logs). We also included a complete set of fixed effects for the month of publication and the dominant topic.

Table 1. Determinants of ‘success’

	<i>Nb. Citations</i>	<i>Attention Score</i>	<i>Interd. Spread</i>
	(1)	(2)	(3)
μ_{AI}^{team}	-0.346*** (0.069)	-0.583*** (0.060)	-0.097*** (0.021)
μ_{AI}^{kn}	0.083 (0.063)	-0.521*** (0.055)	-0.017 (0.019)
μ_{GEN}^{team}	0.482* (0.271)	0.259 (0.238)	-0.060 (0.080)
μ_{GEN}^{kn}	2.165*** (0.176)	2.162*** (0.150)	0.299*** (0.054)
AI Collaborator	0.055 (0.162)	-0.399*** (0.141)	-0.034 (0.050)
Top AI Collaborator	0.298*** (0.076)	-0.070 (0.068)	0.041* (0.023)
Past Impact (log)	0.148*** (0.007)	0.143*** (0.006)	0.012*** (0.002)
Academic Age (log)	-0.265*** (0.025)	-0.231*** (0.022)	-0.033*** (0.007)
Nb. Countries (log)	1.068*** (0.032)	0.423*** (0.028)	0.114*** (0.010)
Nb. References (log)	0.385*** (0.015)	0.068*** (0.013)	0.063*** (0.004)
Observations	12,180	12,180	8,734
Log Likelihood	-38,868		
AIK	77,816		
Adjusted R2		0.183	0.068
F Statistic		71.16***	17.33***

Notes: The statistical model for evaluating the relationship of different interdisciplinary metrics on three indicators of ‘success’: the number of citations received by the publication (Column 1), the Altmetric attention score (Column 2) and the interdisciplinary spread (Column 3). Coefficient estimates of time and topic fixed effects have been omitted from the table.

As shown in Table 1, the most notable result to emerge from our model is that collaborations with researchers experienced in AI (*AI Collaborator*) do not have a significant impact, and those involving a high share of researchers with established track records of AI publications (μ_{AI}^{team}) receive, on average, fewer citations, have less online visibility, and struggle to reach distant disciplines. Only those teams that include a top AI researcher

(*Top AI Collaborator*) present a positive impact on citations received by their publication, albeit that this impact is not strong. Similarly, the ratio of AI-related references (μ_{AI}^{kn}) has a null or negative impact on the Altmetric attention score. All in all, research interdisciplinarity limited to AI does not seem to have any influence on the impact of COVID-19 publications, and when it does, this influence is negative.

What appears to ensure the impact of a publication is, above all else, the interdisciplinarity of the knowledge mobilized via its references (μ_{GEN}^{kn}), that is the actual epistemological diversity of the research conducted by a team. This variable has a very strong positive effect on the number of citations and on the online visibility of a publication and this effect is consistently higher than that of more classic features, such as past impact or the number of affiliated countries. The overall diversity of team members (μ_{GEN}^{team}) has only a marginal positive effect on the number of citations.

Discussion. The COVID-19 pandemic sparked a global research effort to address this unprecedented event. The scientific system responded promptly to the early stages of the virus and the international scientific community called upon its diverse expertise to assess the clinical and pathogenic characteristics of the disease and to formulate therapeutic strategies. Policymakers were also quick to seek advice from ethicists, sociologists, and economists on how best to deal with the crisis (Fry et al., 2020; Chahrour et al., 2020). Against this backdrop, AI applications represented a promising approach to face many of the challenges posed by the pandemic.

A number of studies focused on the AI-COVID-19 nexus have identified various barriers that may well have impeded the disciplines support of COVID-19 research. They include poor data quality and flow, as well as deficient global standards and database interoperability (e.g., genetic sequences, protein structures, medical imagery and epidemiological data); the inability of algorithms to work without sufficient knowledge of the domain; overly exacting computational, architectural, and infrastructural requirements; and the legal and ethical opacity associated with privacy and intellectual property (Bullock et al., 2020; Luengo et al., 2020; Naudé, 2020; Khan et al., 2021; Piccialli et al., 2021).

Here, we have analyzed the role played by different forms of interdisciplinarity, both at the team level and in the research conducted, and their repercussions on various measures of scientific impact. Our research was, in part, motivated by the fact that policy initiatives around the world have emerged – and continue to emerge – aimed at bringing the AI community and the healthcare system closer together. However, we have no direct evidence of the effectiveness of these initiatives. Our study provides an unequivocal takeaway message for academic decision-makers: collaborations involving AI researchers did not result in more impactful science, quite the contrary. What generates high-impact outcomes is not “on paper” interdisciplinarity engendered by team diversity, but rather the epistemological diversity hardwired into a paper. So how can team members best mobilize and blend ideas, tools, and knowledge from their scientific fields? We believe that further needs to comprehend the optimal team composition, conditions, and attributes for successful integration of novel computational technologies into scientific practices.

Acknowledgment. This work was supported by the La Mission pour les Initiatives Transverses et Interdisciplinaires (MITI) of the Centre National de la Recherche Scientifique (CNRS). This work was also supported by the European Union – Horizon 2020 Program under the scheme “INFRAIA-01-2018-2019 – Integrating Activities for Advanced Communities”, Grant Agreement n.871042, “SoBigData++: European Integrated Infrastructure for Social Mining and Big Data Analytics” (<http://www.sobigdata.eu>). Stefano Bianchini received financial support through the SEED project – Grant agreement ANR-22-CE26-0013.

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Supplementary information

Data. Our analysis combines data from four different databases – *CORD-19*, *Semantic Scholar*, *OpenAlex*, and *Altmetric* – and is based on the pre-processing protocol illustrated in Fig. 1A.

The COVID-19 Open Research Dataset (CORD-19) is a growing corpus of publications on COVID-19 and other coronavirus infections (Wang et al., 2020). It includes, in the period that we considered (from 01/12/2019 to 31/08/2021), around 600K documents from different sources, including WHO, PubMed central, bioRxiv and medRxiv.

Within this large corpus, we focused specifically on a subset of 26,887 publications that included, in the abstract or in the title, at least one keyword related to AI. Our list of around 300 AI keywords (Tab. 1A) was retrieved by merging the terms mentioned in the Wikipedia AI Glossary for AI with several other pages entitled as ‘AI vocabulary’ and ‘AI glossary on the web’.

For each paper in this subset, we retrieved additional metadata from Semantic Scholar and OpenAlex. We discarded any documents with missing information and obtained a final corpus of 16,148 AI publications on COVID-19 (COVID-19+AI dataset). For each of these papers, we then retrieved all their references (c. 1 million papers) and all papers citing them (c. 200K papers), as well as the metadata associated with all these papers.

Semantic Scholar metadata included the DOI, which we used for retrieving the ‘attention score’ for each paper in the COVID-19+AI dataset from the website Altmetric.com. This provides a measure of online activity for scholarly content (e.g., mentions on the news, in blogs, and on Twitter; article page-views and downloads; GitHub repository watchers). We used the author identifier in OpenAlex to retrieve the previous publications of all 87,552 authors present in our corpus (around 150K papers) and the institutions to which they are affiliated.

Figure 1A. Data preparation pipeline

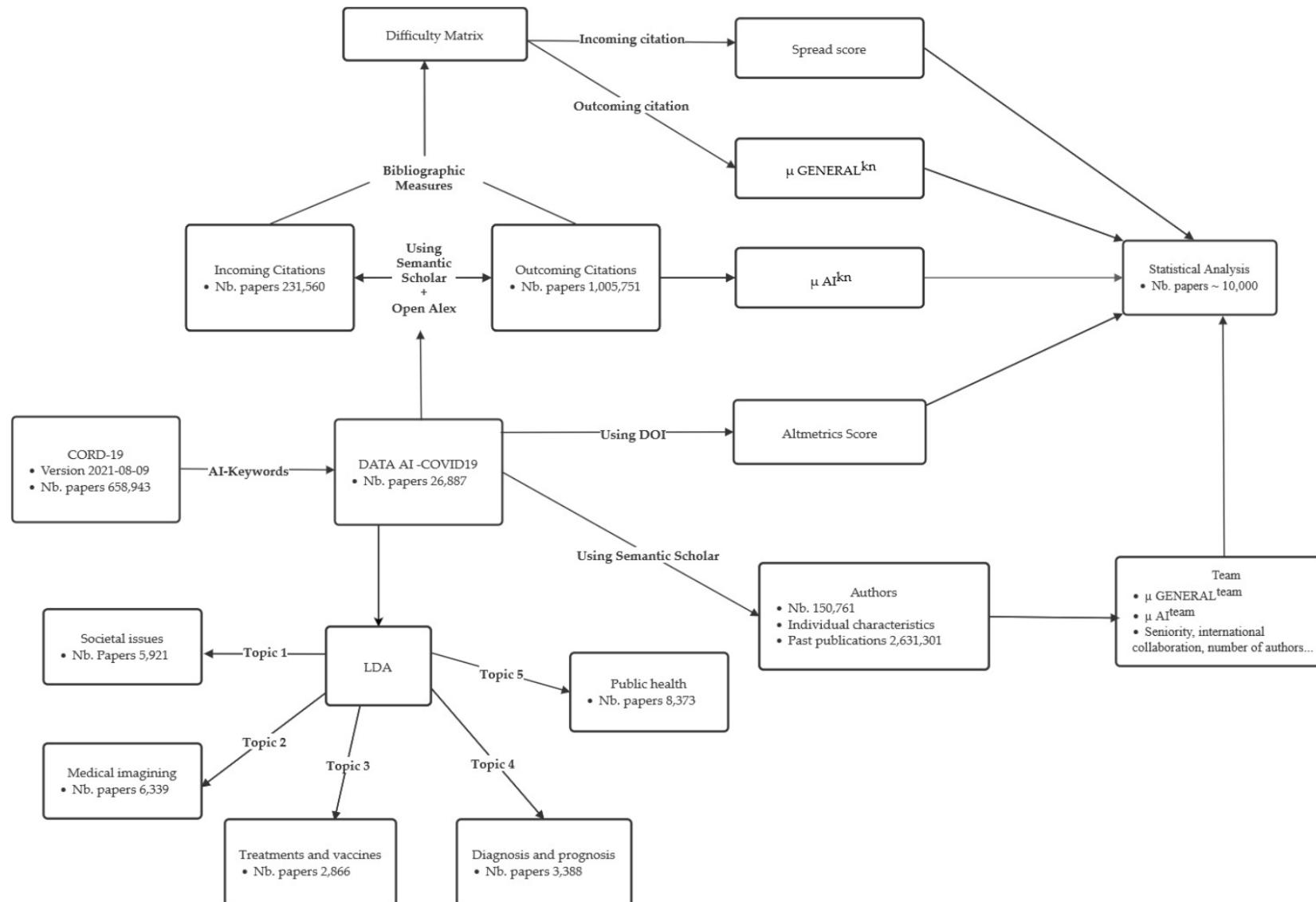


Table 1A. AI terms for document retrieval

abductive logic programming	boolean satisfiability problem	developmental robotics	kl one	ontology learning
abductive reasoning	brain technology	dialogue system	knowledge acquisition	open mind common sense
abstract datatype	branching factor	dimensionality reduction	knowledge engineering	openai
action language	brute-force search	discrete system	knowledge extraction	opencog
action model learning	capsule neural network	distributed artificial intelligence	knowledge interchange format	partial order reduction
action selection	case based reasoning	dynamic epistemic logic	knowledge representation and reasoning	partially observable markov decision process
activation function	chatbot	eager learning	knowledge-based system	particle swarm optimization
adaptive algorithm	cloud robotics	ebert test	lazy learning	pathfinding
adaptive/neuro fuzzy inference system	cluster analysis	echo state network	lisp	pattern recognition
admissible heuristic	cobweb	embodied agent	logic programming	predicate logic
adversarial neural	cognitive architecture	embodied cognitive science	long short term memory	predictive analytics
affective computing	cognitive computing	ensemble averaging	machine learning	principal component analysis
agent architecture	cognitive science	error driven learning	machine listening	principle of rationality
ai accelerator	combinatorial optimization	ethics of artificial intelligence	machine perception	probabilistic programming
ai application	committee machine	evolutionary algorithm	machine translation	prolog
ai applications	commonsense knowledge	evolutionary computation	machine vision	propositional calculus
ai complete	commonsense reasoning	evolving classification function	markov chain	qualification problem
aiml	computational chemistry	existential risk from artificial general intelligence	markov decision process	quantum computing
alphago	computational complexity theory	expert system	mathematical optimization	query language
ambient intelligence	computational creativity	fast and frugal trees	mechanism design	radial basis function network
answer set programming	computational cybernetics	feature extraction	mechatronics	random forest
anytime algorithm	computational humor	feature learning	meta learning	reasoning system
application programming interface	computational intelligence	feature selection	metabolic network reconstruction and simulation	recurrent neural
approximate string matching	computational learning theory	federated learning	metaheuristic	recurrent neural network
approximation error	computational linguistics	first order logic	model checking	region connection calculus
argumentation framework	computational mathematics	forward chaining	modus ponens	reinforcement learning
artificial general intelligence	computational neuroscience	friendly artificial intelligence	modus tollens	reservoir computing
artificial immune system	computational number theory	fuzzy control system	monte carlo tree search	resource description framework
artificial intelligence	computational problem	fuzzy logic	multi agent system	restricted boltzmann machine
artificial neural network	computational statistics	fuzzy rule	multi swarm optimization	rete algorithm
association for the advancement of artificial intelligence	computer automated design	fuzzy set	mycin	robot
asymptotic computational complexity	computer vision	general game playing	naive bayes classifier	robotics
attributional calculus	concept drift	generative adversarial network	naive semantics	rule-based system
augmented reality	connectionism	genetic algorithm	name binding	satisfiability
automata theory	consistent heuristic	genetic operator	named entity recognition	search algorithm
automated planning and scheduling	constrained conditional model	glowworm swarm optimization	named graph	self-management
automated reasoning	constraint logic programming	graph database	natural language	semantic analysis
autonomic computing	constraint programming	graph theory	natural language generation	semantic network
autonomous car	constructed language	graph traversal	natural language processing	semantic query sensor fusion
autonomous robot	control theory	halting problem	natural language programming	semantic reasoner
backpropagation	convolutional	hyper heuristic	network motif	semantic search
backpropagation through time	convolutional neural	ieee computational intelligence society	neural machine translation	semi supervised learning
backward chaining	convolutional neural network	image detection	neural network	sentiment analysis
bag of words model	darkforest	image recognition	neural networking	separation logic
bag of words model in computer vision	dartmouth workshop	incremental learning	neural networks	similarity learning
batch normalization	data augmentation	inference engine	neural turing machine	situation calculus
bayesian programming	data fusion	information integration	neuro fuzzy	speech recognition
bees algorithm	data integration	intelligence amplification	neuromorphic engineering	statistical learning
behavior informatics	data mining	intelligence explosion	nlp	supervised learning
behavior tree	data science	intelligent agent	nondeterministic algorithm	tensorflow
belief desire intention software model	datalog	intelligent control	nouvelle ai	text mining
bias-variance tradeoff	decision boundary	intelligent machine	np completeness	trajectory forecasting
big data	decision support system	intelligent personal assistant	np hardness	transfer learning
big o notation	deep learning	issue tree	object detection	unsupervised learning
binary tree	deepmind technologies	junction tree algorithm	occam's razor	
blackboard system	default logic	keras	offline learning	
boltzmann machine	description logic	kernel method	online machine learning	

Table 2A. Most recurrent bigrams in the corpus

Aggregate		Societal Issues		Medical Imagining		Treatments and Vaccine		Diagnosis and Prognosis		Public Health	
public health	2748	social medium	1600	chest xray	1973	molecular docking	588	mental health	653	health care	885
social medium	2283	public health	1412	xray image	1762	main protease	435	systematic metanalysis	565	public health	738
chest xray	2011	confirmed case	841	ct image	1228	immune response	388	risk factor	539	mental health	522
xray image	1782	social distancing	795	ct scan	1117	spike protein	324	intensive car	419	social medium	433
mental health	1614	infectious disease	601	chest ct	1022	molecular dynamic	305	controlled trial	405	internet thing	416
health care	1607	united states	563	transfer learning	948	signaling pathway	286	clinical trial	396	contact tracing	400
result show	1576	number case	403	computed tomography	903	drug discovery	274	logistic regression	337	social distancing	398
learning algorithm	1446	mental health	390	learning model	842	amino acid	271	health care	335	digital technology	371
learning model	1424	using learning	375	learning algorithm	697	drug repurposing	271	mechanical ventilation	332	digital health	337
using learning	1411	case death	359	experimental result	675	clinical trial	261	viral infection	254	language processing	303
social distancing	1363	air quality	345	learning method	652	healthcare system	312	cross-sectional study	305	health system	292
infectious disease	1334	march 2020	307	tomography ct	639	binding affinity	243	care unit	302	virtual reality	271
ct image	1285	health organization	304	using learning	596	gene expression	236	significant difference	296	face mask	267
chest ct	1257	world health	301	chest x-rays	522	innate immune	226	included study	296	clinical trial	262
ct scan	1236	learning model	289	learning approach	505	virtual screening	220	confidence interval	295	learning algorithm	256
learning method	1139	reproduction number	282	learning technique	465	chinese medicine	214	study conducted	295	medical student	252
confirmed case	1120	learning algorithm	276	publicly available	463	recognition receptor	213	analysis performed	285	higher education	251
computed tomography	1082	language processing	258	sensitivity specificity	449	antiviral drug	202	public health	280	infectious disease	243
learning approach	1061	learning approach	254	chain reaction	408	immune system	192	statistically significant	280	distance learning	227
transfer learning	1048	learning technique	251	cxr image	395	component analysis	191	material method	280	supply chain	226

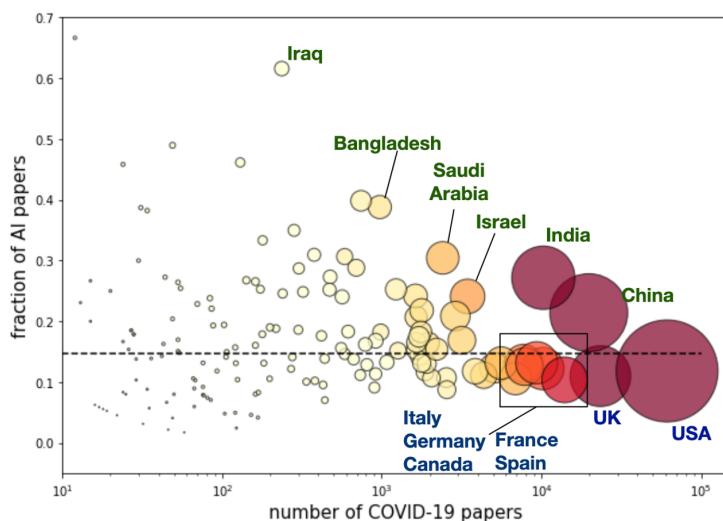
Notes: This table reports the 20 most recurrent non-AI (see Table 1A) bigrams in publication corpus, aggregate and by dominant topic

The statistical model. The empirical analysis tests the determinants of the various impact measures, our three dependent variables: the number of citations received by the publication, the Altmetric attention score and the interdisciplinary spread (measuring how publications are cited in a diverse set of disciplines). The number of citations, \mathcal{N} , is a count variable and was modelled using a negative binomial regression. The continuous variables – attention score \mathcal{M} and interdisciplinarity spread \mathcal{I} – were modeled using ordinary least square regressions.

For each paper, we included other factors in the models that could influence its impact and visibility: namely *AI Collaborator* (=1 if the team includes at least an AI researcher); *Top AI Collaborator* (=1 if the team includes an AI researcher with past number of citations in the top 10° percentile of the citation distribution); *Academic Age* (average academic age of team members, in logs); *Past Impact* (average H-Index of team members based on past publications, in logs); *Nb. Countries* (number of participating countries within a team, in logs); and *Nb. References* (number of cited references, in logs). We also included a complete set of dummies for the month of publication and the dominant topic.

Some geographical trends. While COVID-19 article production is geographically distributed according to the general patterns of scientific productivity observed in previous studies (Fry et al., 2020; Wang et al., 2021) (with the United States, the United Kingdom and China leading the way, followed by Western European countries and India), the use of AI in COVID-19 research presents a different distribution (Fig. 2A). The countries of Asia and the Middle East – China and India, in particular – appear as leaders of AI-based COVID-19 research, while the USA and Western European countries lag somewhat behind.

Table 2A. Geographical distribution of publication activity AI-COVID-19



Notes: Plot A: Fraction of COVID-19 papers containing AI. Inset: Total number of COVID-19 papers containing AI. Plot B: Fraction of COVID-19 papers containing AI by country. Nodes are sized and colored according to the total number of COVID-19-AI papers. The dotted line represents the sample average.