AI research in Canadian hospitals: The development of metropolitan competencies*

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Abstract

This study explores the deployment of artificial intelligence in Canadian hospitals from 2000 to 2021, focusing on metropolitan areas. We investigate how local public and private research ecosystems and links to national and international AI hubs influence the adoption of AI in healthcare. Our analysis shows that AI research outputs from public institutions have a significant impact on AI competences in hospitals. In addition, collaborations between hospitals are critical to the successful integration of AI. Metropolitan areas such as Toronto, Montreal and Vancouver are leading the way in AI deployment. These findings highlight the importance of local AI research capabilities and international hospital collaborations, and provide guidance to policymakers and healthcare leaders to drive the diffusion of AI technology in healthcare.

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1 Introduction

The healthcare sector represents a critical area where the deployment of AI and robotics can significantly improve patient care, increase diagnostic and treatment capabilities, or help in decision-making. The advent of machine learning, and more specifically deep learning, has enabled the emergence of data-driven solutions for health informatics and biomedical research[1]. AI is used in a wide range of applications in dermatology, radiology, anaesthesiology, psychiatry, surgery, genomics, and medical records[2;3]. It can improve patient care not only by reducing costs and improving safety but also by intervening upstream through early detection of chronic disease or preventive medicine[4].

Challenges such as the lack of interpretability in AI outputs, the high costs of surgical systems, the requirement of tacit knowledge from surgeons to perform procedures adequately, and the scarcity of usable clinical data necessary for building accurate AI models hinder the widespread adoption of these technologies[5–7]. To overcome these issues, Canada is supporting initiatives to develop a Canadian health data platform for advancing precision medicine through the Digital Health and Discovery Platform (DHDP) coalition. This initiative connects partners from healthcare institutions, companies, and universities across Canada[8]. The case of Canada is particularly interesting, given the country's influential contributions to the field of AI. Canada has a large community of AI scientists and practitioners with 3 AI hubs growing in Toronto, Montreal, and the Edmonton region[9;10]. In particular, in 2023, Toronto's performance in AI start-ups has been noticeable, being considered one of the top spots at the world level[11].

While Canada is well known for its AI research, AI devices are not integrated uniformly into Canadian healthcare institutes[12]. Practitioners and medical students are not sufficiently trained in Canada, and there is some reluctance to adopt AI technologies within the medical community due to uncertainties around liability issues[12;13]. Most of the studies on AI in healthcare in Canada are rather qualitative and provide a limited understanding of overall diffusion trends[14]. There is a need for a more detailed grasp of the interdependence between the public sector, companies, and hospitals in the process of diffusion of AI in medicine.

In this article, we provide the first systematic quantitative analysis of the deployment of AI in Canadian hospitals at the metropolitan area level for the period 2000-2021. The diffusion of AI technologies in hospitals is linked to: a) the existence of a thriving local ecosystem supporting the development of the technologies inclusive of public and private organizations, b) the ease of access to national and international hot-spots for frontier research in AI, and c) the ease of access to advanced users in national and international hospitals that have already adopted the technologies. Absorptive capacity of the hospital and of its employees also plays an important role in successful adoption. Hospitals with previous experience in these technologies will be more prone to adopt advanced AI systems.

We find evidence of the importance of both metropolitan and external knowledge sources for the uptake of AI in hospitals. AI research in local public organizations and companies in the past is correlated with a higher level of deployment of AI technologies in hospitals. Public research is relatively more important than company research, but this result may depend on the focus on hospital pre-clinical activities. Most interestingly, from a managerial perspective, is the fact that external knowledge flows coming from hospitals active in AI are highly correlated with the uptake of AI in local hospitals. Hospitals that succeeded in developing relationships with national and international hospitals active in AI are much more active in AI research. However, only a small group of metropolitan areas has been able to activate this channel of knowledge exchange. Toronto is leading, followed by Montreal, Vancouver, and Ottawa; the other metropolitan areas have not been able to exploit this source of knowledge so far. Hospital and health managers, especially in less important metropolitan areas, should be more proactive in supporting collaborations with both local public research and other hospitals at the national and international levels.

2 Data and Methodology

We analyze the relation between the characteristics of a metropolitan ecosystem's competencies in AI in the period 2000-2016 and the last 5 years of activity in AI in hospitals (2017-2021). Data availability and citation windows constrain the analysis to 2021. Table 1 shows the performance of the top 20 metropolitan areas in the world in the last period. The two largest Canadian cities are respectively in sixth and sixteenth positions, showing a major role for Canada.

AI technologies can be used in hospitals to support the management of the institution, in the pre-clinical phase of research and care experimentation, and to deliver care to patients in the clinical phase (diagnosis, pre-operative, operative, and postoperative). To study the deployment of AI in hospitals, we use bibliometric data of scientific publications indexed in OpenAlex. Capturing the deployment of AI in hospitals with publications can be considered an acceptable proxy for activities going on at the border between pre-clinical and clinical phases. As such, it provides a lower bound estimation of the real use of AI. We classified articles as pertinent to AI using OpenAlex's "concepts." We used a broad definition of AI including first-level concepts of "Artificial intelligence" and "Machine learning" and their respective ancestors. This allows us to extract 4,496,336 documents for the period 2000-2021. Authors with at least one Canadian affiliation accounted for 188,316 publications.

Using the Research Organization Registry (ROR) classification, we were able to identify 15,354,871 affiliations out of the 16,064,390 in our AI sample. We classified affiliations into: 1) involving only public research (Only PR: all affiliations are either "Education" or "Government"); 2) private companies (Comp: at least one "Company" affiliation); and 3) hospitals (Hosp: at least one "Healthcare" affiliation). We use this information to carry out the organizational analysis described below. We then aggregate our analysis at the census metropolitan area (CMA) level. Our final sample is composed of 2,910 metropolitan areas participating in AI worldwide, with 38 of them in Canada.

Our focus lies in understanding the relationship between past performance in AI technologies by local public research organizations and businesses and their subsequent deployment

Table 1: Top Contributors in AI research in Hospitals (World wide)

Metropolitan Area	Country	# Articles (Hosp. - after 2017)
Boston	United States	7,834
New York	United States	4,122
Rochester	United States	3,149
Seoul	South Korea	3,060
Beijing	China	2,655
Toronto	Canada	2,375
Houston	United States	2,024
London	United Kingdom	1,942
Dallas	United States	1,799
Cleveland	United States	1,735
Baltimore	United States	1,712
Berlin	Germany	1,457
Philadelphia	United States	1,442
Rotterdam	Netherlands	1,403
Los Angeles	United States	1,321
Montréal	Canada	1,313
New Taipei	Taiwan	1,291
South Bend	United States	1,234
Chicago	United States	1,133
Nashville	United States	1,094

by hospitals. We proxy performance with both output and specialization indicators. Additionally, we investigate the diffusion of international knowledge into the local ecosystem by analyzing the positioning of Canadian cities in the collaborative network of AI research. This entails assessing cities' eigenvector centralities in national and international co-publication networks to understand their positioning. In particular, we analyze hospital centrality in the international network of hospitals engaged in AI technologies to delineate information flows among hospitals utilizing AI.

Finally, we conduct a regression analysis to account for other potential factors that may influence the correlations between performance and deployment in hospitals. Specifically, we run a set of OLS regressions for only Canada and for all the countries worldwide (see Online Appendix A.5.1 and A.5.2). Our control variable included the population size of CMAs, utilized as a rough proxy for economic development, concentration of economic activities, and research funding opportunities. We include as independent variables output measures and network measures. We do not include specialization measures as the descriptive analysis shows their lack of relevance. For comprehensive details regarding our methodology, please consult the Online Appendix (Download here).

3 Results

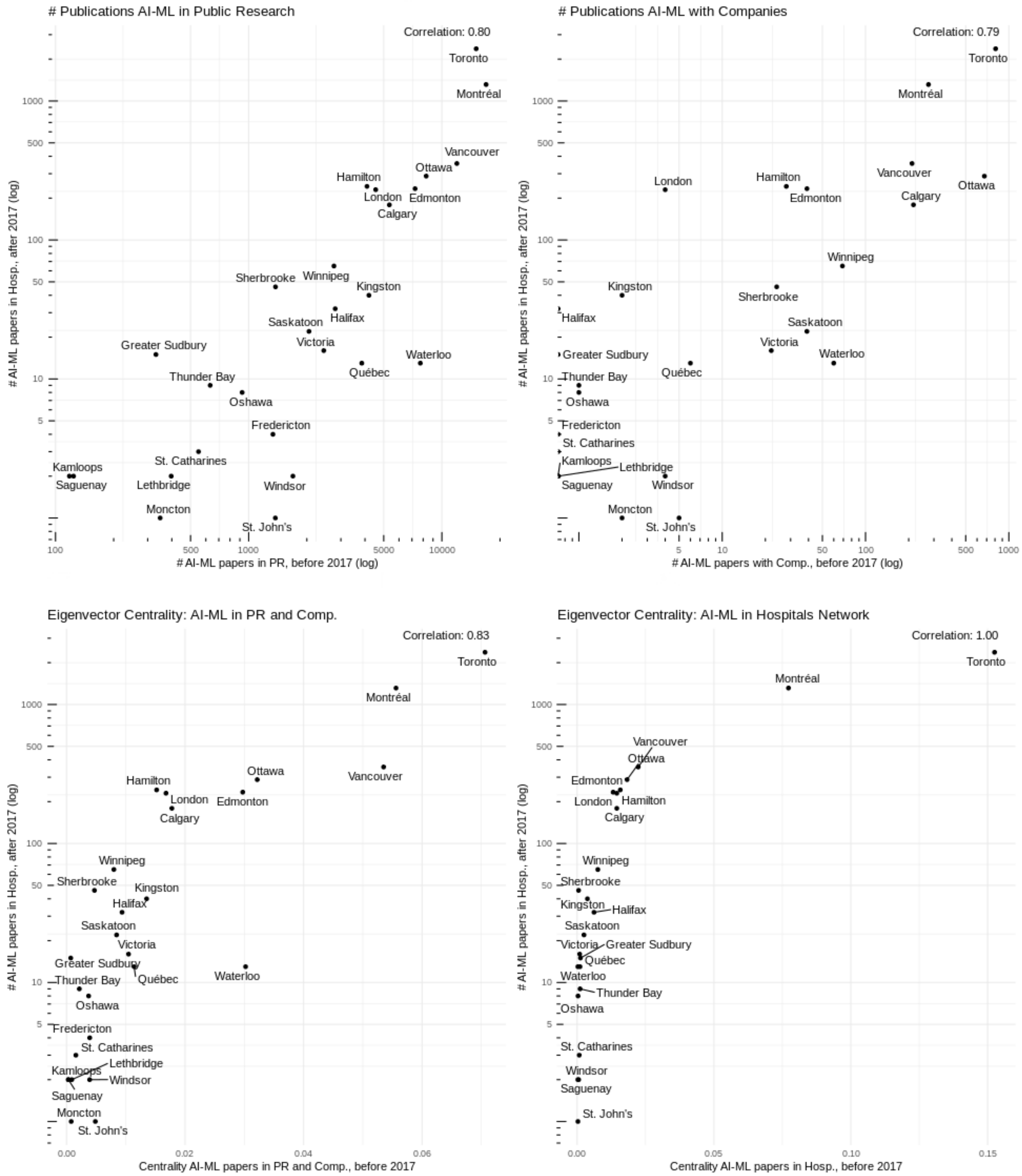
In line with findings from previous research[15;16], our analysis reveals a marked exponential growth in the number of AI publications globally, as illustrated in Figure A1 (See Online Appendix). The United States (US), China (CN), and the European Union (EU) are at the forefront of this expansion. Canada (CA) exhibits a growth pattern that parallels the US and EU trends in terms of AI publications. Especially, there is a noticeable shift in the global distribution of AI research, as the proportional contributions of the US and EU (and Canada) are gradually declining in contrast to the rising shares from China and other emerging participants in the field.

Figure 1 (1st row – left panel) shows a strong correlation (0.80) between hospital AI publication output in the period 2017-2021 and papers in AI published by authors affiliated only to PR in the period 2000-2016. The graph includes only 27 CMAs that had at least one hospital publication in the final period and one hundred publications in PR before 2017. 11 of the total 38 CMAs involved show no evidence (as measured by publications) of competences/involvement in AI at the hospital level. Toronto and Montreal, the two largest Canadian CMAs (respectively 6.2 M and 4.3M inhabitants in 2021), outperform all other CMAs considering publication output in AI in hospitals in the period 2017-2021. Toronto is the CMA with the highest output with about 2,605 articles. The leading role of Toronto is confirmed by the results of the Newsweek World's Best Smart Hospitals 2021 ranking,[1] of the 12 Canadian hospitals included 9 are in the Toronto CMA the other 3 are in Montreal, Ottawa and Vancouver. Two distinct clusters including respectively 6 and 8 CMAs follows the first two CMAs. In cluster 3 Waterloo stands out as the good performance of PR researchers in AI (at the level of Ottawa) is less correlated to AI research in Hospitals. Finally, a fourth cluster is composed by CMAs that published less than one paper a year in AI with hospital affiliation in the last period, indicating very weak activity in that area. Clusters 2, 3 and 4 are composed by CMAs of different average size, with an average population of about 1.4M, 0.5M and 0.2M respectively.

All CMAs in the top three groups have a medical school; while the two smallest medical schools of St. John's and Sudbury/Thunder Bay are included in the lower performance group four. Medical school sizes in the second and third clusters are not significantly different. These results indicate that the existence of a minimum size (more than 100 students) medical school in the CMA is a precondition for having some AI research activity in health, however, the size of the medical school does not discriminate between the two mid-performance clusters 2 and 3. We have repeated the same analysis (see Figure 1, 1st row – right panel) looking at company publications. Companies publish much fewer papers in AI; for example, the highest number of publications by companies is in Toronto with about 800, while the highest number of publications by public research organizations is in Montreal with about 17,000. However, the correlation coefficient of 0.78 is similar to the one of public research organizations. Moreover, there is some change in the relative position of the CMAs in the 3 clusters. These results indicate that companies have varying roles in the ecosystem supporting the deployment of AI in hospitals according to the different CMAs.

[1]Ranking analysis performed by Statista

Figure 1: Output metrics and centrality metrics



AI specialization at the metropolitan area level is not correlated to the deployment of AI in hospitals (see Figure A2 in the Online Appendix). The only information worth noticing is the high relative specialization of Waterloo in AI PR research (compared to other CMAs in cluster 3) that is not mirrored in a higher diffusion of AI in hospitals. Overall, relative specialization does not provide any added explanatory power to understand what supports AI deployment in hospitals.

The analysis of collaborative networks in AI research, illustrated in Figure 2, shows that hospitals in Toronto, Montreal, and Vancouver are among the most connected and occupy central and influential positions in the international collaboration network. Our findings (see Figure 1 – 2nd row, right panel) reveal a robust positive correlation between the centrality of CMAs in terms of collaboration between public research and businesses in AI during the initial period and the subsequent increase in AI paper production within hospitals. This suggests that cities linked as major hubs for AI production experience heightened engagement in AI research within hospital settings, implying a diffusion of AI knowledge into healthcare contexts. When examining collaboration networks focusing solely on papers in AI authored by hospital-affiliated researchers, a stronger positive correlation emerges between the centrality of CMAs and subsequent AI production in hospitals. This higher correlation indicates the more important role played by the hospital network in diffusing AI knowledge into healthcare systems. It also indicates the importance of internal drivers and capabilities of hospitals required for the absorption of external knowledge. However, much of this result is driven by the particular role played by Toronto, Montreal and Vancouver, the only Canadian CMAs highly connected into the international hospital network.

Finally, the results of the regression analysis indicate the significant role of the local ecosystem, encompassing both public research organizations and companies, with the former being much more relevant than the latter. External sources of knowledge also play a vital role, with centrality in the hospital network in AI research in the past being strongly correlated with current AI activity in hospitals in the full model specification.

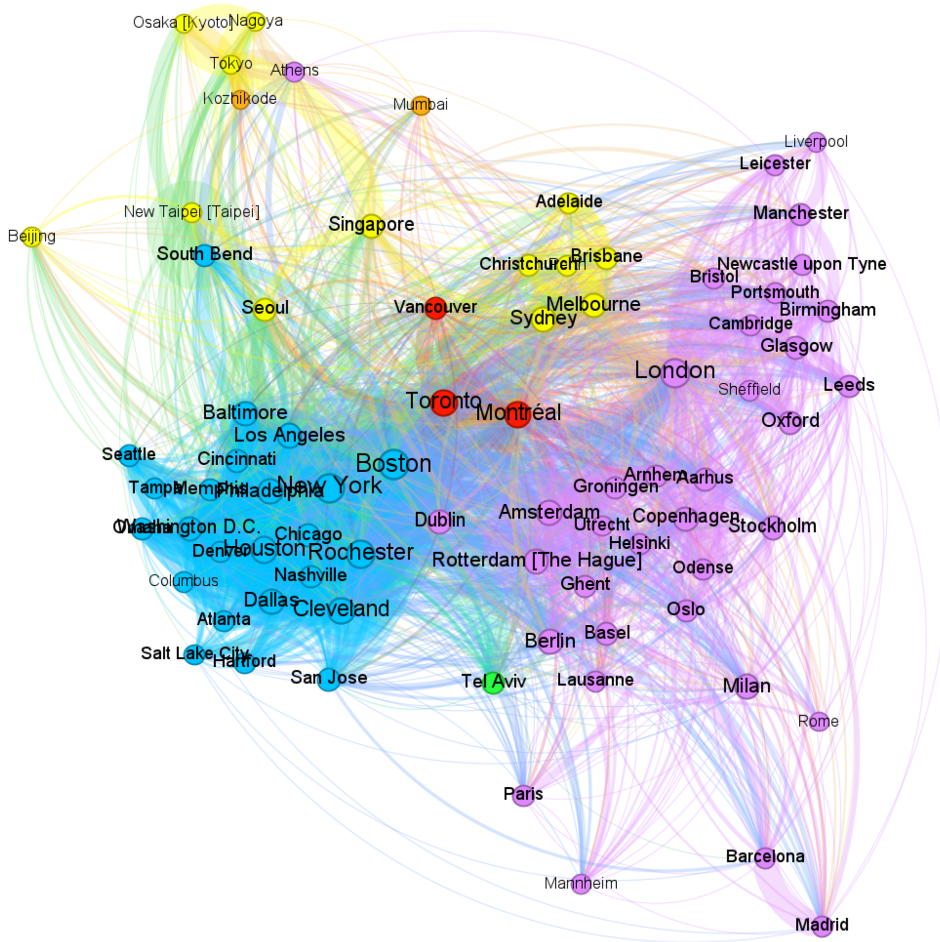
4 Conclusions

Using global AI publications as a proxy for organizational capabilities, this paper presents the first systematic quantitative analysis of AI deployment within Canadian hospitals. Our findings reveal a correlation between the utilization of AI technologies in healthcare at the metropolitan level in Canada and the presence of a local ecosystem of both public and private research. Beyond local competencies, hospitals' capacity to leverage the national and international network of AI technology users in hospitals also emerges as a significant factor.

We validated the Canadian findings by examining approximately 3,000 metropolitan areas worldwide. Drawing from this extensive sample, we confirmed that the presence of AI companies in a metropolitan area correlates with increased AI activity in hospitals, albeit with an impact magnitude approximately 4 to 6 times smaller than that of public research. Notably, the magnitude of this effect depends on the proxy used to gauge AI deployment in hospitals, which captures the utilization of AI technologies at the border between pre-clinical and clinical phases.

Furthermore, our analysis underscores the significance of external knowledge flows. However, the evidence suggests that it is more crucial for hospitals to establish connections with external hospitals utilizing AI technologies rather than with external public or private research organizations. This finding aligns with the perspective that sourcing knowledge from

Figure 2: AI/ML collaboration network among hospitals across urban areas



distant organizations is more complex than sourcing it locally. Consequently, the connection between hospitals (which is easier to manage due to affinity) yields more substantial outcomes compared to the link between hospitals and public or private organizations.

The positive hospital network effect is driven by the two highly internationally connected large cities of Toronto and Montreal. The third largest Canadian city, Vancouver, is well connected in the public research and companies network but not in the hospital network. The role played by hospital AI user networks underscores the importance of making simpler international collaborations among hospitals to facilitate the uptake of AI technologies. In the Canadian context, medical schools and hospitals of the second cluster should increase their international collaborations to successfully tap into the international hospital network that is the driving force in the diffusion of AI-based methods.

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A Online Appendix

A.1 Data

Our data are extracted from the OpenAlex database, as of June 2022, which includes approximately 238 million documents. To focus on AI, we narrowed our scope to publications tagged with the OpenAlex Concepts "Artificial Intelligence" and "Machine Learning", including their hierarchical ancestors. This selection results in a corpus of 16,493,355 articles. Following Arts et al. (2023), we removed articles with duplicate titles, abstracts, or DOIs, and limited the selection to journal articles, published conference proceedings, and preprints. This procedure reduced our dataset to 8,736,902 articles. We further refined the dataset to include only those articles for which at least one author's geolocation was identifiable, resulting in 5,759,007 articles. We confined our analysis to the period between 2000 and 2021, leaving us with 4,744,748 articles. We finally retain only articles with at least one author affiliated with a Census Metropolitan Area, reducing our dataset to 4,496,336 articles. Of this sample, 188,316 articles were authored by a Canadian-affiliated author. Table A1 presents the breakdown of the publications into the three organizational categories.

We then aggregate our analysis at the census metropolitan area (CMA). For Canada we rely on Statcan 2021 data to assign to each affiliation on an article a census metropolitan area based on the ROR geolocation[2], for other CMAs we make use of GHSL-OECD Functional Urban Areas from 2015.[3] Our final sample is composed of 2,910 metropolitan areas participating in AI worldwide, with 38 of them in Canada.[4]

Table A1: Number of articles in each classification

Category	**Total**	**Only PR**	**Comp.**	**Hops.**
Worldwide	4,496,336	3,771,645	223,439	187,527
Canada	188,316	156,764	3,518	11,509

[2]Data can be found here: https://www12.statcan.gc.ca

[3]Data can be found here: https://jeodpp.jrc.ec.europa.eu

[4]There are 41 CMA in Canada but Brantford, Chilliwack and Drummondville are not included in our sample as they are not active in AI. Some CMA includes cities from two different countries, in the case of US and Canada, we kept them separated

A.2 Indicators used

Our variable of interest is the number of publications in AI involving a hospital from a given CMA after 2017. We calculate total research output per CMA before 2017, splitting between Only public research articles and articles involving at least one company from the given CMA. We also compute weighted measures that consider the number of citations received by a given article, the output measurement at the CMA level is then the sum of all average number of citations per year received by articles published in the given CMA. Second, we calculate the Revealed Symmetric Comparative Advantage (RSCA) Index derived from the revealed comparative advantage index,[?] to account for the specialization in knowledge production in a given CMA. For each CMA we derive three different metrics of specialization in AI, a specialization index for public research, one for companies, and one for hospitals.[5] Here also we compute weighted RSCA metrics by using the average number of citations per year received by articles. Finally, we constructed a collaboration network among researchers who publish AI. Our approach involves constructing a network at the article level and then aggregating it at the CMA level. Specifically, the strength of a link between two CMAs is determined by the number of articles involving researchers from both areas. We then calculate the nodes eigenvector centrality to assign scores to each CMA based on their centrality and influence, considering both the quantity and quality of connections. Thus, utilizing eigenvector centrality allows us to effectively assess how CMAs are interconnected with other central urban areas within the network. We explore two distinct networks: one incorporating public research and companies, and another focusing solely on hospitals. Additionally, in citation-weighted networks, links are weighted based on the average number of citations received per year, providing a more accurate reflection of the relevance of these collaborations.

Output: To measure a metropolitan area's scientific output, we count the number of scientific articles published by authors affiliated with institutions in that urban area.

Revealed Symmetric Comparative Advantage: The Revealed Comparative Advantage (RCA) proposed by[?] is a quantitative measure used to identify the extent to which a region has a specialized advantage in a particular sector or activity, relative to a larger comparative framework. In this article the RCA index is adapted to quantify the CMA's specialization in specific fields of research.

$$RCA_{i,AI} = \frac{\left(\frac{P_{i,AI}}{P_{i\cdot}}\right)}{\left(\frac{P_{\cdot AI}}{P_{\cdot\cdot}}\right)}$$

where $P_{i,AI}$ is the number of publications from city i in AI. $P_{i\cdot}$ is the total number of publications from city i in all fields. $P_{\cdot,AI}$ is the total number of global publications in AI. $P_{\cdot\cdot}$ is the total number of global publications in all fields.

We used a symmetric version of the RCA as proposed by,[?] the Revealed Symmetric Comparative Advantage (RSCA):

[5] Note that to compute RSCA we used the whole OpenAlex database to account for other publications not related to AI

$$RSCA_{i,AI} = \frac{RCA_{i,AI} - 1}{RCA_{i,AI} + 1}$$

Eigenvector centrality: Eigenvector centrality is a network analysis measure used to determine the relative importance of nodes within a network. Unlike simpler centrality measures that focus on immediate connections (such as degree centrality), eigenvector centrality considers both the quantity and quality of connections. The core idea is that a node is considered more central if it is connected to other nodes that are themselves central.

More formally the eigenvector centrality of a node x_i is:

$$x_i = \frac{1}{\lambda} \sum_{j=1}^{n} a_{ij} x_j$$

where x_i is the eigenvector centrality score of node i. λ is the largest eigenvalue of the adjacency matrix A. a_{ij} is an element of the adjacency matrix A of the network. a_{ij} is the number of coauthored articles from node i to node j if there is a connection, and 0 otherwise. Since we are using an undirected network, A is symmetric, and $a_{ij} = a_{ji}$.

Weighted metrics: For each article, we calculate the average number of citations it receives per year since its publication and use it as a weighting factor in our analysis. The cumulative metric for a given urban area is then derived by summing these weighted averages across all articles attributed to that location. Similarly, when assessing specialization indexes, each article's contribution is weighted by its annual citation rate. Finally, in the network analysis, the weight assigned to the link between two urban areas in a specific article is determined by the article's average yearly citation count.

A.3 Descriptives Statistics

Figure A1: Number and Share of AI publication over time

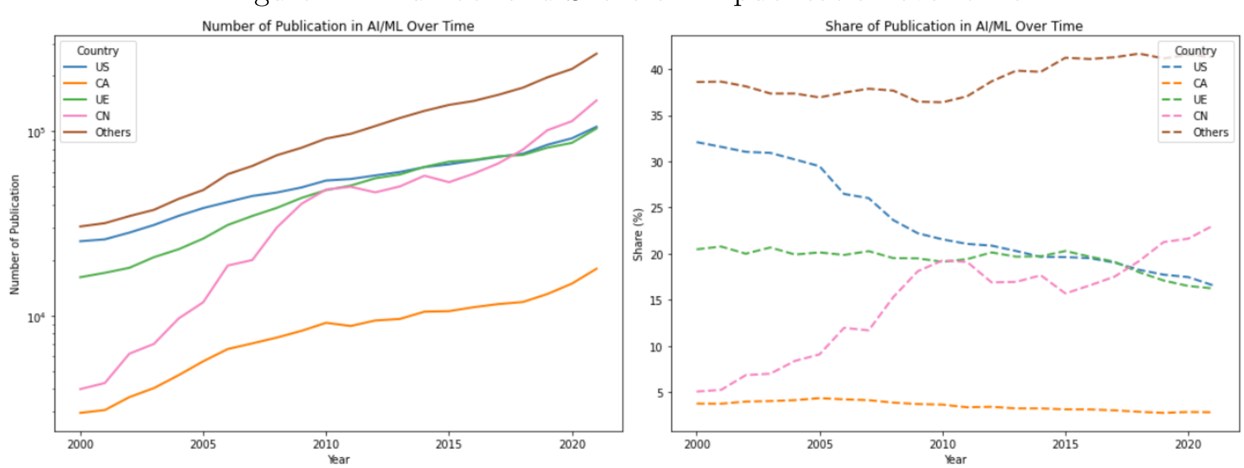


Table A2 and Table A3 show the descriptive statistics at census metropolitan area level for our sample for Canada and for the entire database respectively. In both cases, we kept in our analysis cities with more than 100 publications from public research institutions only between 2000 and 2016 included, along with hospitals having participated at least once in AI articles after 2017.

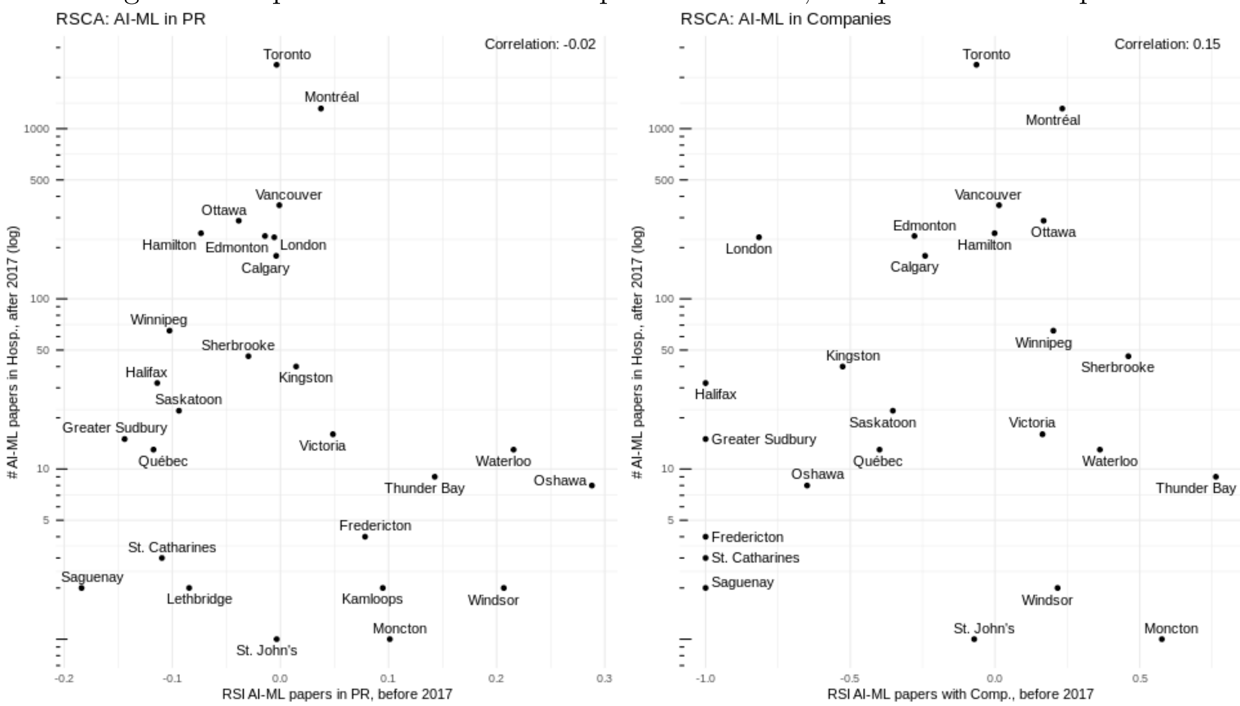
Table A2: Descriptive Statistics (Canada)

	Min	25%	Med	Mean	75%	Max
# Articles (Hosp. - before 2017)	1	3.5	16	204.2	204.5	2375
# Articles (PR - before 2017 - log)	118	778.5	2448	4020.4	4947	16940
# Articles (PR - before 2017 - log - Weighted)	153	1746	4784	9319	10801	40233
# Articles (Comp. - before 2017)	0	0.5	5	92.26	49.5	808
# Articles (Comp. - before 2017 - Weighted)	0	0	2.868	120.25	102.085	1146.753
Eigenvector cent. (PR/Comp. - before 2017)	0	0.003	0.008	0.015	0.017	0.071
Eigenvector cent. (PR/Comp. - before 2017 - Weighted)	0.001	0.002	0.006	0.014	0.013	0.076
Eigenvector cent. (Hosp. - before 2017)	0	0.001	0.003	0.015	0.015	0.153
Eigenvector cent. (Hosp. - before 2017 - Weighted)	0	0.001	0.004	0.019	0.015	0.214
Relative Spe. Index (PR - before 2017)	-0.184	-0.089	-0.004	0.004	0.063	0.288
Relative Spe. Index (PR - before 2017 - Weighted)	-0.357	-0.124	-0.011	-0.01	0.114	0.284
Relative Spe. Index (Comp. - before 2017)	-1	-0.649	-0.072	-0.21	0.202	0.763
Relative Spe. Index (Comp. - before 2017 - Weighted)	-1	-0.874	-0.226	-0.276	0.183	0.667
Relative Spe. Index (Hosp. - before 2017)	-1	-0.125	-0.059	-0.154	0.015	0.287
Relative Spe. Index (Hosp. - before 2017 - Weighted)	-1	-0.193	-0.035	-0.138	0.086	0.727

Table A3: Descriptive Statistics (World wide)

	Min	25%	Med	Mean	75%	Max
\# Articles (Hosp. - before 2017)	1	5	18	124.7	76.5	7834
\# Articles (PR - before 2017 - log)	101	399	1172	3256	2938	117101
\# Articles (PR - before 2017 - log - Weighted)	26	510.6	1954.2	6580.6	5709.3	162916.1
\# Articles (Comp. - before 2017)	0	0	1	173.7	23.5	13391
\# Articles (Comp. - before 2017 - Weighted)	0	0	0	411.49	29.51	65065.49
Eigenvector cent. (PR/Comp. - before 2017)	0	0.001	0.004	0.014	0.011	0.363
Eigenvector cent. (PR/Comp. - before 2017 - Weighted)	0	0.001	0.004	0.012	0.01	0.377
Eigenvector cent. (Hosp. - before 2017)	0	0	0.001	0.012	0.007	0.458
Eigenvector cent. (Hosp. - before 2017 - Weighted)	0	0	0.001	0.011	0.006	0.447
Relative Spe. Index (PR - before 2017)	-1	-0.155	-0.022	-0.023	0.114	0.537
Relative Spe. Index (PR - before 2017 - Weighted)	-1	-0.162	-0.013	-0.021	0.115	0.68
Relative Spe. Index (Comp. - before 2017)	-1	-0.574	-0.184	-0.248	0.109	0.771
Relative Spe. Index (Comp. - before 2017 - Weighted)	-1	-0.796	-0.254	-0.287	0.124	0.805
Relative Spe. Index (Hosp. - before 2017)	-1	-0.357	-0.112	-0.199	0.041	0.772
Relative Spe. Index (Hosp. - before 2017 - Weighted)	-1	-0.532	-0.118	-0.229	0.099	0.916

Figure A2: Specialization metrics in public research, companies and hospitals



A.4 Network Analysis

Network graphs in this section show CMAs with the highest eigenvector centrality. Each node corresponds to an urban area (CMA). The size of each node reflects the urban area's eigenvector centrality. Node positions are determined using ForceAtlas2 and nodes positioned centrally hold greater influence. Edge sizes denote the number of articles involving researchers from both connected areas. We construct two distinct networks, the first is based on articles from public research and companies in a given CMA (PR + Comp.), while the second is restricted to collaborations between hospitals in different CMAs (Hosp.). In the international network (See Figure A5 for PR + Comp. and Figure 2 for Hosp. network), we represented the top 5% and top 10% most central CMAs respectively, to maintain readability. Nodes and edges are color-coded by geographical region, with red representing Canadian urban areas.

Canadian Network

Figure A3: AI/ML collaboration network among public research institutes and companies across urban areas in Canada

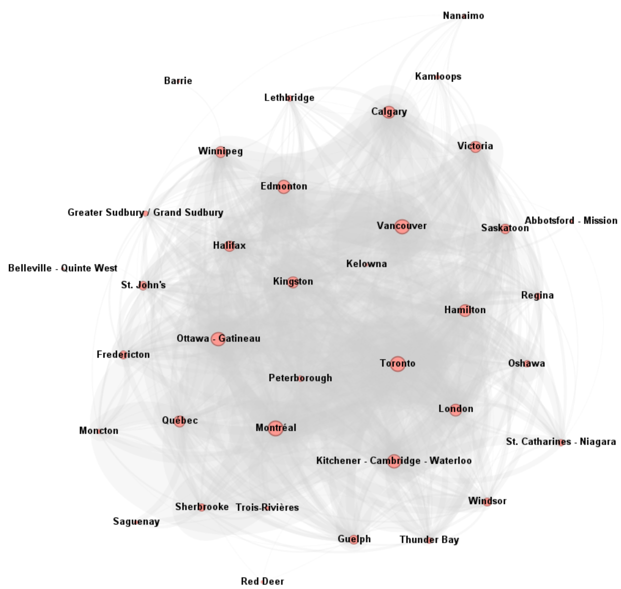
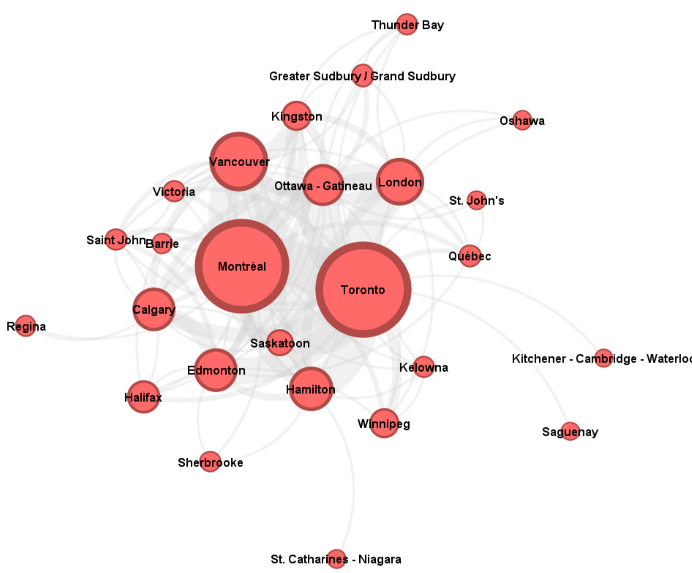
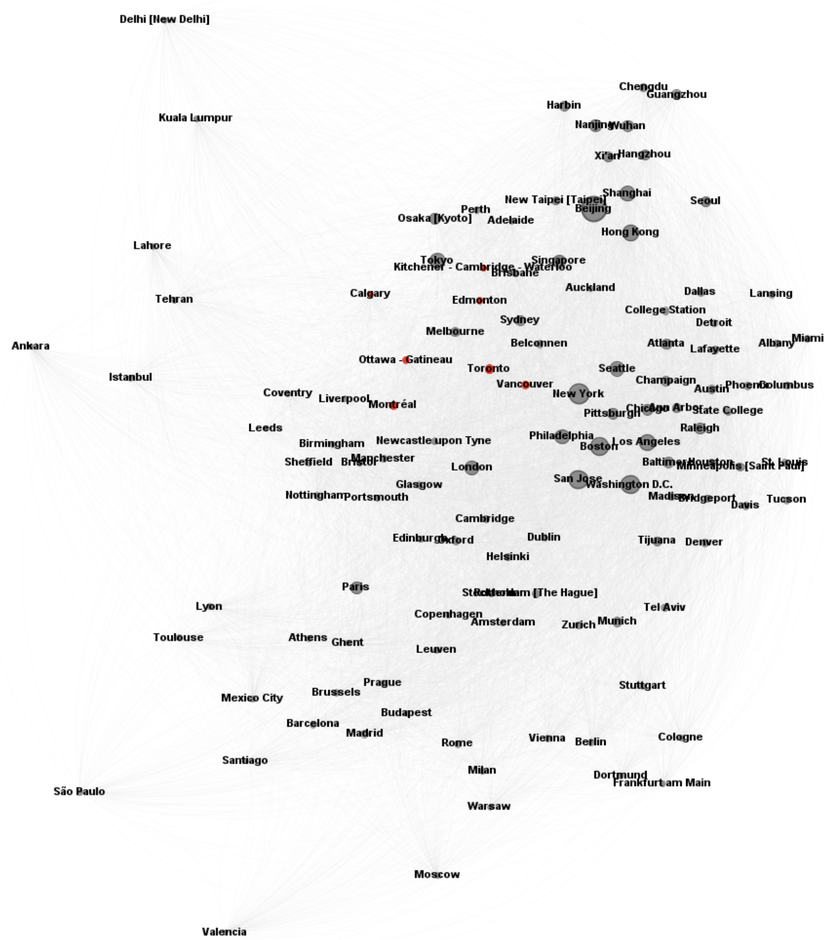


Figure A4: AI/ML collaboration network among hospitals across urban areas in Canada



International Network

Figure A5: AI/ML collaboration network among public research institutes and companies across urban areas. Top 5%



A.5 Regression Analysis

In this section, we present the tables of the regressions (OLS), the dependent variable is the number of AI articles written in a given CMA with at least one hospital. We also did the same analysis using the number of AI articles weighted by the mean annual number of citations. The analysis was conducted at the Canadian level, and similar regressions were run at the global level to provide a broader perspective.

A.5.1 Canada level

Table A4: Number of AI articles written by hospitals in Canadian CMAs after 2017 (OLS)

	Dependent variable:							
	# Articles (Hosp. - after 2017 - log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pop. 2016 (log)	0.981^{***}	1.110^{***}	0.810^{**}	0.745^{*}	0.766^{**}	0.545	0.014	0.057
	(0.326)	(0.351)	(0.385)	(0.394)	(0.318)	(0.459)	(0.412)	(0.406)
# Articles (PR - before 2017 - log)	0.558^{**}		0.472			0.291	0.486^{*}	0.142
	(0.265)		(0.286)			(0.406)	(0.248)	(0.364)
# Articles (Comp. - before 2017)		0.265	0.156			0.105	0.147	0.114
		(0.178)	(0.185)			(0.192)	(0.157)	(0.160)
Eigenvector cent. (PR/Comp. - before 2017)				107.260^{**}		55.916		108.495
				(47.728)		(75.122)		(82.146)
Eigenvector cent.^{2} (PR/Comp. - before 2017)				-909.931		-338.585		$-2{,}002.118$
				(589.253)		(884.390)		(1,232.890)
Eigenvector cent. (Hosp. - before 2017)					98.253^{***}		93.570^{***}	107.214^{***}
					(33.392)		(30.369)	(33.383)
Eigenvector cent.^{2} (Hosp. - before 2017)					-526.839^{**}		-479.293^{**}	-401.985^{*}
					(196.981)		(179.929)	(192.977)
Constant	-13.619^{***}	-11.712^{**}	-11.126^{**}	-7.436	-7.286^{*}	-6.844	-1.546	-0.197
	(2.807)	(4.208)	(4.079)	(4.756)	(3.951)	(5.381)	(4.554)	(4.818)
Observations	27	27	27	27	27	27	27	27
R^2	0.762	0.742	0.769	0.776	0.798	0.785	0.848	0.869
Adjusted R^2	0.742	0.720	0.739	0.746	0.771	0.734	0.812	0.820
Residual Std. Error	1.041	1.084	1.047	1.032	0.980	1.058	0.890	0.870
F Statistic	38.416^{***}	34.474^{***}	25.548^{***}	26.510^{***}	30.243^{***}	15.324^{***}	23.403^{***}	17.934^{***}

Notes: This table reports coefficients of the effect of Canadian metropolitan area characteristics on AI publication in local hospitals. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Effects are estimated using OLS.

Table A5: Number of AI articles written by hospitals in Canadian CMAs after 2017 (OLS – Citation Weighted)

	Dependent variable:							
	# Articles (Hosp. - after 2017 - log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pop. 2016 (log)	0.947^{***}	1.278^{***}	0.848^{**}	0.953^{**}	1.150^{***}	0.628	0.317	0.255
	(0.307)	(0.336)	(0.370)	(0.369)	(0.305)	(0.441)	(0.435)	(0.431)
# Articles (PR - before 2017 - Weighted)	0.545^{**}		0.515^{**}			0.482	0.527^{**}	0.376
	(0.227)		(0.237)			(0.313)	(0.229)	(0.290)
# Articles (Comp. - before 2017 - Weighted)		0.153	0.074			0.062	0.109	0.117
		(0.154)	(0.148)			(0.157)	(0.142)	(0.146)
Eigenvector cent. (PR/Comp. - before 2017 - Weighted)				100.942^{*}		20.153		52.753
				(55.014)		(74.560)		(71.558)
Eigenvector cent.^{2} (PR/Comp. - before 2017 - Weighted)				-919.767		-31.860		$-1{,}148.932$
				(612.233)		(824.406)		(916.602)
Eigenvector cent. (Hosp. - before 2017 - Weighted)					45.657		47.781^{*}	98.572^{**}
					(27.624)		(25.198)	(40.664)
Eigenvector cent.^{2} (Hosp. - before 2017 - Weighted)					-175.893		-174.991	-332.788^{**}
					(117.991)		(107.775)	(147.478)
Constant	-13.452^{***}	-13.610^{***}	-12.104^{***}	-9.856^{**}	-11.967^{***}	-9.215^{*}	-5.806	-4.294
	(2.700)	(4.076)	(3.856)	(4.471)	(3.804)	(4.973)	(4.743)	(4.964)
Observations	27	27	27	27	27	27	27	27
R^2	0.773	0.729	0.775	0.759	0.750	0.785	0.814	0.837
Adjusted R^2	0.754	0.707	0.746	0.727	0.718	0.734	0.770	0.777
Residual Std. Error	1.017	1.111	1.034	1.070	1.090	1.058	0.983	0.967
F Statistic	40.804^{***}	32.296^{***}	26.432^{***}	24.135^{***}	23.014^{***}	15.340^{***}	18.399^{***}	13.974^{***}

Notes: This table reports coefficients of the effect of Canadian metropolitan area characteristics on AI publication in local hospitals. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Effects are estimated using OLS.

A.5.2 World level

Table A6: Number of AI articles written by hospitals in CMAs after 2017 (OLS)

	Dependent variable:							
	# Articles (Hosp. - after 2017 - log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pop. 2016 (log)	0.877***	0.966***	0.799***	0.941***	0.919***	0.794***	0.661***	0.658***
	(0.052)	(0.053)	(0.058)	(0.048)	(0.041)	(0.058)	(0.055)	(0.055)
# Articles (PR - before 2017 - log)	0.311***		0.271***			0.203***	0.258***	0.295***
	(0.041)		(0.043)			(0.052)	(0.040)	(0.049)
# Articles (Comp. - before 2017)		0.134***	0.082***			0.061**	0.034	0.043
		(0.027)	(0.027)			(0.028)	(0.026)	(0.026)
Eigenvector cent. (PR/Comp. - before 2017)				19.468***		7.941*		−4.544
				(3.336)		(4.119)		(4.011)
Eigenvector cent.^{2} (PR/Comp. - before 2017)				−44.318***		−14.448		9.479
				(12.749)		(14.156)		(13.582)
Eigenvector cent. (Hosp. - before 2017)					30.187***		28.477***	29.561***
					(3.045)		(2.975)	(3.101)
Eigenvector cent.^{2} (Hosp. - before 2017)					−55.112***		−53.190***	−54.204***
					(8.274)		(8.021)	(8.283)
Constant	−12.052***	−11.528***	−10.773***	−11.195***	−10.902***	−10.331***	−8.849***	−9.008***
	(1.190)	(1.285)	(1.257)	(1.234)	(1.142)	(1.268)	(1.179)	(1.187)
Observations	807	807	807	807	807	807	807	807
R^2	0.684	0.671	0.688	0.682	0.713	0.691	0.733	0.734
Adjusted R^2	0.637	0.622	0.641	0.634	0.670	0.644	0.692	0.692
Residual Std. Error	1.045	1.067	1.039	1.050	0.997	1.035	0.963	0.963
F Statistic	14.620***	13.739***	14.735***	14.295***	16.570***	14.629***	17.938***	17.621***

Notes: This table reports coefficients of the effect of Canadian metropolitan area characteristics on AI publication in local hospitals. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Effects are estimated using OLS.

Table A7: Number of AI articles written by hospitals in CMAs after 2017 (OLS – Citation Weighted)

	Dependent variable:							
	# Articles (Hosp. - after 2017 - log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pop. 2016 (log)	0.897***	0.963***	0.808***	0.993***	0.961***	0.812***	0.693***	0.685***
	(0.050)	(0.052)	(0.056)	(0.045)	(0.041)	(0.056)	(0.054)	(0.054)
# Articles (PR - before 2017 - Weighted)	0.272***		0.237***			0.196***	0.228***	0.251***
	(0.036)		(0.037)			(0.041)	(0.035)	(0.039)
# Articles (Comp. - before 2017 - Weighted)		0.128***	0.083***			0.062**	0.049**	0.058**
		(0.024)	(0.025)			(0.026)	(0.023)	(0.024)
Eigenvector cent. (PR/Comp. - before 2017 - Weighted)				17.864***		6.405*		−4.174
				(3.367)		(3.886)		(3.986)
Eigenvector cent.^{2} (PR/Comp. - before 2017 - Weighted)				−36.500***		−8.991		7.246
				(11.383)		(12.189)		(13.160)
Eigenvector cent. (Hosp. - before 2017 - Weighted)					26.300***		24.749***	26.026***
					(3.038)		(2.943)	(3.180)
Eigenvector cent.^{2} (Hosp. - before 2017 - Weighted)					−46.243***		−45.131***	−46.309***
					(8.379)		(8.071)	(9.168)
Constant	−12.049***	−11.488***	−10.658***	−11.898***	−11.461***	−10.492***	−9.047***	−9.061***
	(1.188)	(1.277)	(1.248)	(1.215)	(1.155)	(1.248)	(1.187)	(1.188)
Observations	807	807	807	807	807	807	807	807
R^2	0.685	0.672	0.690	0.679	0.703	0.693	0.726	0.727
Adjusted R^2	0.638	0.623	0.644	0.631	0.659	0.646	0.685	0.685
Residual Std. Error	1.043	1.065	1.036	1.053	1.014	1.032	0.974	0.974
F Statistic	14.679***	13.815***	14.867***	14.149***	15.817***	14.757***	17.352***	17.052***

Notes: This table reports coefficients of the effect of Canadian metropolitan area characteristics on AI publication in local hospitals. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Effects are estimated using OLS.