Geography of Artificial Intelligence Adoption

Suthee Sangiambut[1] and Renee Sieber[2]

[1]Department of Geography, McGill University, suthee.sangiambut@mail.mcgill.ca
[2]Department of Geography, McGill University, renee.sieber@mcgill.ca

Artificial Intelligence (AI) promises to vastly improve analysis, policy making, and government operations. In government, AI has been defined through a system lens to mean "machine-based system[s] that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments" (Johnson 2020). Such systems have potential application and impact in a wide range of government functions, from improving the provision of public services, to algorithmic governance over society and the enforcement of rules (such as law enforcement), all of which have wide-ranging effects on society (Engstrom et al. 2020). However, current approaches to AI adoption remain jurisdictionally bound, limiting the ability of governments to account for impacts, externalities, harms, and dependencies across multiple scales.

Traditional views of technology adoption, such as organizational readiness (Weiner 2009) and technology acceptance (Davis 1989), have been re-applied to AI (Alsheibani, Cheung, and Messom 2018). However, resulting models of adoption can be limited to jurisdictionally bound step-wise processes (e.g. Jöhnk, Weißert, and Wyrtki 2021) that do not incorporate political or political economy lens. We argue that AI is not jurisdictionally bound and should be understood in its own *geography of AI*.

First, the AI system stack is dispersed geographically, leading to dependencies beyond government jurisdictions. Algorithms and models are primarily developed in Global North nations, primarily the US (Fujii and Managi 2018). Governments face capacity and expertise limitations to develop their own AI solutions (Zuiderwijk, Chen, and Salem 2021), leading to technology imports and outsourcing to private sector (potentially foreign) actors – a form of technological dependency, which can impact analysis, policy making, and policy outcomes. Furthermore, improved data processing and decision making process can reduce cognitive loads on government officials, allow them to engage the public more directly and improve public service provision (Mehr 2017). Such benefits may be contingent on government capacity and as such unevenly dispersed across countries.

AI's development and use can have dispersed material impacts, such as environmental impacts of computing infrastructure (Bender et al. 2021). AI shape how we view the world and in the process create new geographies (León and Rosen 2020), resulting in distantiated forms of governance. Meanwhile, the exploitation of cheap labour in the Global South to train image recognition models can put the effects of AI far beyond the implementing country (Altenried 2020), leading to new local and global geographies of inequality.

As a sociocultural artifact, AI disperses cultural values of its makers, potentially challenging or subsuming values within organizations and across society. Bias in labelling can reinforce sexist stereotypes about the role of women in society (Bender et al. 2021), requiring cross-cultural cooperation in AI governance and ethics (ÓhÉigeartaigh et al. 2020). Bias embedded in algorithms can lead to flawed understandings of crime, racial bias in predictive policing, and lasting harms to communities (Richardson, Schultz, and Crawford 2019).

Finally, AI is an issue of national strategic interest as a driver of economic innovation and public sector modernization (Fatima, Desouza, and Dawson 2020), placing it in the centre of US-China competition (Wang and Chen 2018). In this geopolitical context, agencies may face political influence from the outside-in, impacting procurement choices, data governance, and access to systems.

Through the geography of AI, we broaden the critical set of endogenous and exogenous factors that governments may consider in their adoption strategies. Building this awareness in government will lead to more transparent and accountable government services and reduce potential downstream harms for society.

References

Alsheibani, Sulaiman, Yen Cheung, and Chris Messom. 2018. "Artificial Intelligence Adoption: AI-Readiness at Firm-Level." *PACIS 2018 Proceedings*, June. https://aisel.aisnet.org/pacis2018/37.

Altenried, Moritz. 2020. "The Platform as Factory: Crowdwork and the Hidden Labour behind Artificial Intelligence." *Capital & Class* 44 (2): 145–58. https://doi.org/10.1177/0309816819899410.

Bender, Emily M., Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. 2021. "On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? ." In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 610–23. FAccT '21. New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/3442188.3445922.

Davis, Fred D. 1989. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology." *MIS Quarterly* 13 (3): 319–40. https://doi.org/10.2307/249008.

Engstrom, David Ff, Daniel E. Ho, Catherine M. Sharkey, and Mariano-Florentino Cuellar. 2020. "Government by Algorithm: Artificial Intelligence in Federal Administrative Agencies | Administrative Conference of the United States." e Administrative Conference of the United States. https://www.acus.gov/report/government-algorithm-artificial-intelligence-federal-administrative-agencies.

Fatima, Samar, Kevin C. Desouza, and Gregory S. Dawson. 2020. "National Strategic Artificial Intelligence Plans: A Multi-Dimensional Analysis."

Economic Analysis and Policy 67 (September): 178–94. https://doi.org/10.1016/j.eap.2020.07.008.

Fujii, Hidemichi, and Shunsuke Managi. 2018. “Trends and Priority Shifts in Artificial Intelligence Technology Invention: A Global Patent Analysis.” *Economic Analysis and Policy* 58 (June): 60–69. https://doi.org/10.1016/j.eap.2017.12.006.

Jöhnk, Jan, Malte Weißert, and Katrin Wyrtki. 2021. “Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors.” *Business & Information Systems Engineering* 63 (1): 5–20. https://doi.org/10.1007/s12599-020-00676-7.

Johnson, Eddie Bernice. 2020. *H.R.6216 National Artificial Intelligence Initiative Act of 2020*. https://www.congress.gov/bill/116th-congress/house-bill/6216.

León, Luis F. Alvarez, and Jovanna Rosen. 2020. “Technology as Ideology in Urban Governance.” *Annals of the American Association of Geographers* 110 (2): 497–506. https://doi.org/10.1080/24694452.2019.1660139.

Mehr, Hila. 2017. “Artificial Intelligence for Citizen Services and Government.” Harvard Ash Center for Democratic Governance and Innovation. https://ash.harvard.edu/files/ash/files/artificial_intelligence_for_citizen_services.pdf.

ÓhÉigeartaigh, Seán S., Jess Whittlestone, Yang Liu, Yi Zeng, and Zhe Liu. 2020. “Overcoming Barriers to Cross-Cultural Cooperation in AI Ethics and Governance.” *Philosophy & Technology* 33 (4): 571–93. https://doi.org/10.1007/s13347-020-00402-x.

Richardson, Rashida, Jason M. Schultz, and Kate Crawford. 2019. “Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice.” *New York University Law Review Online* 94: 15.

Wang, You, and Dingding Chen. 2018. “Rising Sino-U.S. Competition in Artificial Intelligence.” *China Quarterly of International Strategic Studies* 04 (02): 241–58. https://doi.org/10.1142/S2377740018500148.

Weiner, Bryan J. 2009. “A Theory of Organizational Readiness for Change.” *Implementation Science* 4 (1): 67. https://doi.org/10.1186/1748-5908-4-67.

Zuiderwijk, Anneke, Yu-Che Chen, and Fadi Salem. 2021. “Implications of the Use of Artificial Intelligence in Public Governance: A Systematic Literature Review and a Research Agenda.” *Government Information Quarterly* 38 (3): 101577. https://doi.org/10.1016/j.giq.2021.101577.