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Co-production for Artificial Intelligence project implementation: lessons from Latin America

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Abstract

In this paper, we ask what is the role of stakeholders such as citizens and the private sector in designing and implementing artificial intelligence projects in the public sector? Empirically, we use a comparative case study methodology focused on the experience of EmpatIA, a program led by the Latin American Open Data Initiative (ILDA). This analysis was done with privileged access to documents such as using financial and narrative progress reports, community calls, proposal slide decks as well as semi-structured interviews with each team. All the case studies in this paper have a common structure: objectives of the project, type of AI tool used, main beneficiaries, and evaluation of co-production dimensions. We use Nabatchi et al (2017) co-production typology to empirically analyse each case study. Our research finds that co-production in the field of artificial intelligence can occur at any level of co-production and phase of the service cycle, with the majority in the co-delivery of services. Practical lessons learned include the importance of data standardisation and the potential of co-production projects to contribute knowledge transfer from the private to the public sector.

Keywords

Artificial intelligence, collaborative governance, data governance, coproduction, Latin America

Introduction

Artificial Intelligence (AI) can refer to a vast array of issues (Wirtz et al 2018) including systems that think like humans, systems that act like humans, systems that think rationally or systems that act rationally (Russell and Norvig 2010) or - more simply- the study of how to make computers do things which, at the moment, people do better (Rich et al 2009). Current AI-projects can be different types of technologies such as image recognition, pattern recognition, natural language processing, robotic process automation and robotics. AI is not a novel field, but it is now expanding as several factors play a key role: data is now more readily available, computational power has increased and connectivity allows businesses and experts to work across the globe (Smith 2018). Furthermore, a significant group of companies are now investing in several AI related technologies in several areas such as health,agriculture, finance etc.

As AI real life applications expands, governments face two issues: regulating the algorithms and governing by algorithms. Regulation of algorithms has led to ethical guidelines (e.g. UNESCO ethical principles on AI) and emergent regulation (e.g. the proposed European Union AI Act) trying to develop frameworks for the use and development of these techniques. As regulation advances so does the use of algorithms by governments in day to day activities such as handling migration, job seeking applications programs or education (Kuziemski and Mizuraka, 2020). These techniques allow governments to analyse and process data faster for their day to day tasks. Specifically, Misuraca et al (2019) find that:

> AI-enabled innovation within governments can support redesigning governance processes and policy making mechanisms, as well as improve public services delivery and engagement with citizens is growing. When used in a responsible way, the combination of new, large data sources with advanced machine learning algorithms could radically improve the operating methods of the public sector, thus paving the way to proactive public service delivery models and relieving resource constrained organisations from mundane and repetitive tasks. (Misuraca et al, 2019, pg 6).

As these uses spread, so does the potential of misuse and eventual harms (Ehsan et al 2022) as is increasingly documented. One possible way to mitigate potential harms is to bring together multiple stakeholders to the table, when it comes to designing and implementing AI projects in government. In this paper, we therefore ask: how do multiple stakeholders, such as citizens and the private sector, work together in designing and implementing artificial intelligence projects in the public sector?

To answer this question, we build from the literature of co-production in public administration (Nabatchi et al 2017), to explore the implementation of AI projects in the public sector in Latin America. In particular, we seek to explore the ways in which multiple stakeholders can work together in an equal partnership to create ethical applications of AI. In the context of this research we mostly refer to AI as machine learning tools able to analyse, cluster, automate and eventually predict activities or outputs (Smith & Neupane 2018). We use the term machine learning, algorithm and AI in an interchangeable manner.

We draw from the literature of data governance to think through collaborative processes that involve data sharing as well as other digital tools among multiple stakeholders. For example, Wu et al (2021) argue that there is a need for collaboration among public and private actors as the growth of the digital economy has transformed private actors into a major source of data, rather than the government being the main producers of data. However, using co-production as an analytical tool allows us to think beyond production of data, that while necessary, is just one step in the creation of artificial intelligence projects. In this paper, using co production as an analytical tool allows us to consider the ways in which the expertise inside and outside the public sector can be brought together to create artificial intelligence projects in Latin America.

Looking at the Latin American contexts allows us to explore AI-enabled innovation in a diverse and unequal (Scrollini, Cervantes & Mariscal 2021) setting. Empirically, we gather and analyse multiple qualitative data from the experience of EmpatIA, a program led by the Latin American Open Data Initiative (ILDA) that sponsored 7 projects from July 2020 to February 2021. Latin America offers a unique setting to explore AI implementation given the peculiar setting too; for example, a few countries have AI strategies in place and are being executed while others have isolated initiatives or AI is not a priority at all (Scrollini et al 2021, Prudencio2021). Therefore there is an opportunity to explore a degree of different methodological approaches that could serve the development of the region as it advances in its paths to the adoption of AI in the public sector.

Our research finds that co-production in the field of artificial intelligence can occur at any level of co-production and phase of the service cycle, however, most of the case studies we analysed were successful in the co-delivery of services. Conceptually, we contribute to the literature of collaborative governance by empirically analysing the 3 x 4 co-production typology presented by Nabatchi et al (2017) with seven case studies of co-production of seven artificial intelligence for the public good projects in Latin America.

This paper is organised as follows; first, we discuss what we mean by co-production in artificial intelligence projects. Then, we go over the methodology and research setting, focusing on the comparative case study methodology, followed by an examination of the seven case studies we explore in this paper. Lastly, we discuss the lessons learned in the implementation of Empatía in Latin America.

2. Defining co-production

Co-production is a term first coined by Elinor Ostrom (Ostrom et al, 1978) who defined it as "the process through which inputs used to produce a good or service are contributed by individuals who are not in the same organisation". Whitaker (1980) identifies three activities as co-production: 1) citizens requesting assistance from public agents; 2) citizens providing assistance to public agents; and 3) citizens and agents interacting to adjust each other's service expectations and actions. In a more contemporary definition, authors such as Howlett, Kekez & Poocharoen (2017) identify that the meaning has evolved in recent years to include both individuals (i.e. citizens and quasi-professionals) and organisations (citizen groups, associations, non-profit organisations) collaborating with government agencies in both the design and management of services as well as their delivery. Thus, Howlett et al (2017) argue that co-production has become both a managerial device that enriches provision of public or private service and a set of policy tools. Nabatchi, Sancino and Sicilia (2017) define co-production as as "an umbrella concept that captures a wide variety of activities that can occur in any phase of the public service cycle and in which state actors and lay actors work together to produce benefits" (Nabatchi et al, 769). We follow this umbrella definition throughout the paper and analyse co-production activities specifically related to artificial intelligence projects in the public sector.

Additionally, we follow Nabatchi et al (2017) typology of co-production which places co-production projects in a 3 x 4 matrix by level of co-production (individual,group, collective) and phases of the service cycle, this typology can be observed in Table 1. The phases of the service cycle are defined as follows: 1) co-commissioning refers to activities aimed at strategically identifying and prioritising needed public services, outcomes, and users, 2) co-design refers to activities that incorporate the experience of users and their communities into the creation, planning, or arrangements of public services, 3) co-delivery refers to joint activities between state and lay actors that are used to directly provide public services and/or to improve the provision of public services and 4) co-assessment focuses on monitoring and evaluating public services.

		Phase of the Service Cycle			
		Co-Commissioning	Co-Design	Co-Delivery	Co-Assessment
Level of Coproduction	Individual	A doctor and a patient work together to identify and prioritize health problems and needs.	A doctor and a patient work together to develop a strategy or plan for meeting health needs.	A doctor and a patient work together to implement dietary, exercise, smoking cessation, or other activities to meet health needs.	A doctor and a patient evaluate the efficacy of the plan and the degree of health improvement.
	Group	School officials and teachers work with a group of parents who have children with special needs to identify challenges and opportunities in education services.	School officials and teachers work with a group of parents who have children with special needs to design educational activities based on parental experience and best practice.	School officials and teachers work with a group of parents who have children with special needs to provide in-class and extra-curricular educational activities.	School officials and teachers work with a group of parents that have children with special needs to evaluate the provision of services.
	Collective	A local parks department convenes citizens to identify and prioritize desired recreational opportunities in a community.	A local parks department works with citizens to design a series of bicycle routes throughout the community.	A local parks department works with citizens to construct and maintain bicycle routes throughout the community.	A local parks department works with citizens to assess the safety and quality of bicycle routes throughout the community.

Figure 1 - 3 X 4 Coproduction Typology

3. Research setting and methodology

We studied 7 projects awarded by the program Empatía, an open research funding led by the Latin American Open Data Initiative (ILDA) with technical support from Centro Latam Digital (CLD) and financial support from the International Development Research Centre (IDRC) and the Inter-American Development Bank (IADB). As a program. Empatia had the objective of contributing towards the creation of an inclusive, ethically-grounded and rights-based AI field in Latin America. The main objectives of the program are: 1) promoting a better understanding of how the public sector should develop AI policies for development, considering ethical, political, social and economic aspects, 2) promoting the capacities of decision makers in the design and application of AI and 3) promoting projects that explore the resolution of public problems through the use of AI in the public sector. One of the components of the project had the

objective of supporting AI government projects with knowledge and evidence to achieve inclusive AI solutions to replicate and scale across the region.

Understanding the EmpatIA program as co-production in AI for the public good, provides opportunities for different sectors to share technical and thematic knowledge that requires collaboration among two or more parties. Empatia created synergies for cooperation between public and private enterprises, with the explicit objective of creating AI tools that can contribute to a variety of social issues such as climate change, transparency and accountability, health and water management. The co-production aspect of this program is most neatly defined in the regional call for proposals. The open call for applications in the summer of 2020, received more than 70 proposals that were reviewed by an expert panel. Of these proposals, 41% came from the private sector, 39% from civil society organisations, 11% from academia and 10% from governments. Of the 74 proposals received, 35 of the proposals were related to Covid-19 emergency management, followed by 26 on democratic institutionality and government transparency, 6 on climate change, 4 on natural resource management, 3 on gender issues and 3 about other issues.

The theory of change of Empatía was built on the idea that there is a challenge in terms of understanding how to harness AI in Latin America without the proper policies and design practices. We identify that this challenge requires a strengthening of open data initiatives that ensures the availability and accessibility of data, as well as increased governmental awareness of potential uses of AI for development.

After the evaluation round, seven projects were selected by the jury to participate in Empatía. The selected projects comprise a wide range of subjects including: open justice, climate change and mitigation, publicization of contracting data and official governmental newspapers and early identification of cardiovascular diseases. We understand EmpatIA as a co-production project because it allows for profit or non-profit organisations, to collaborate with government agencies in both the design and management of services as well as the delivery of services.

3.1 Data sources and analysis

In this paper, we designed a comparative in depth case study strategy to analyse the 7 projects that were implemented as part of the Empatia program. Two of the authors were involved in the Empatia program since its conception, which gave privileged access to the project proposals, initial interviews, social impact slide decks, community calls both internal and external, as well as financial and narrative progress reports throughout the implementation of each case study. After the projects were finished or about to finish, one of the authors led semi-structured interviews with each of the seven selected teams. The semi-structured interviews had five main themes: project implementation experiences and challenges, contributions to their organisational structure, project scope, sustainability and continuity of the project and evaluation of the project implementation. Table 1 shows a summary of the multiple data sources used for each case study. The financial and narrative reports allowed us to measure and evaluate the objectives, budget, reported activities, deliverables and reflections on the implementation of the projects. The 7 semi-structured interviews with 16 participants were transcribed and edited by the researchers.

For the analysis, we used the primary and secondary sources to identify patterns in each case study using the 3 x 4 typology as analytical guides to classify each project. The project proposals allowed us to identify the partnership structure, objectives and individual level of co-production. The narrative reports were used to understand how each team developed their AI tools, and the challenges they faced while co-producing these tools with their direct partners. Additionally, the final narrative reports, social impact slide decks and the internal and external community calls allowed us to identify the main beneficiaries of each project, as well as the phase of the service cycle of each project. Finally, the financial reports in combination with the final narrative were useful to identify the major challenges in implementation of the projects. The analysis of these materials allowed us to do inductive theorising of the lessons learned, which are presented in section 5.

Table 1 - Data Sources

Interviews	1 hour semi-structured interviews with each team (7 edited interview transcripts, 16 participants)
Secondary data	7 Project proposals
	7 Social impact slide decks
	14 Financial reports (Mid-project and final)
	14 Narrative reports (Mid-project and final)
	3 Transcripts of Community calls (Internal)
	3 Transcript of community calls (Public)

4. Artificial Intelligence for Development: 7 cases in Latin America

In this section, we use a comparative case studies methodology to identify where the EmpatIA projects fit in the Nabatchi et al (2017) 3 x 4 typology of co-production. This typology considers two main variables. Firstly, the levels of co-production: individual, group or collective. The second variable is the phase of the service cycle: co-commissioning, co-design, co-delivery and co-assessment.

The projects that participated in EmpatIA were created to contribute to the public good in several thematic areas such as public procurement, health, environment, resource management and democratic participation. Table 3 presents a summary of all the participating projects, including their country, objectives, partners, beneficiaries and type of AI tool implemented.

Table 2 - Summary of participating projects

Name of project	**Country**	**Objectives**	**AI Tool**	**Partners**	**Main beneficiaries (Direct + Indirect)**
Control Cívico	Paraguay	Increase citizen participation in the control and monitoring of the public procurement process by bringing data closer to citizens through a Twitter bot.	Training model, an ETL (Extract, Transform, and Load) process for data extraction updated automatically and being executed on a server and the Twitter bots.	Centre of Sustainable Development, National Directorate of Public Procurement of Paraguay and National Public Procurement Agency of Colombia.	Direct: National Directorate of Public Procurement of Paraguay and National Public Procurement Agency of Colombia. Indirect: journalists and the technical community interested in the data.

IA²	Argentina	Accompany and guarantee the anonymization process of legal resolutions in Spanish	Developing the user interface, implementing data extraction, developing the model in relation to the server, training the model and developing and improving the infrastructure for model training.	Cambá Cooperative, Buenos Aires Judicial Power District 10	Direct: Juzgado nº 10 de la Ciudad de Buenos Aires Indirect: journalist, citizens, NGOs, Poder Judicial Costa Rica, Poder Judicial Nuevo León (Mexico) Residents of Buenos Aires
Goblab UAI + SMA	Chile	Predict the level of air quality and the occurrence of critical episodes, based on emission data from polluting industries, air quality stations and meteorological data from the communes of Concón, Quintero and Puchuncaví.	Build regression and classification models, consolidate data with new sources and explore predictive models with a new database to create a deep learning model	Goblab UAI , Chile's Environment Superintendency (SMA)	Direct: SMA Indirect: Citizens of Chile
Prosper IA	Mexico	Prevention and widespread early diagnosis of chronic diseases (Diabetes mellitus, hypertension and cardiovascular diseases)	Adjusted the risk models, evaluated the models in specific subpopulations, created adaptive questionnaires hosted in web platforms and are constantly monitoring the use of risk calculators	Mexican Diabetes Federation, Hospital de Nutrición de México and the Institute of Public Health Citizenship	Direct: Mexican Diabetes Federation, Hospital de Nutrición de México and the Institute of Public Health Citizenship Indirect: 220 million people in Latin America and the Caribbean at risk of developing lethal and disabling complications from chronic diseases.
Querido Diario	Brazil	Centralise the content of the official gazette of Brazilian municipalities to facilitate citizens' access to public information usually published by individual municipalities.	Classify, contextualise and expand the information contained in Brazilian official municipal newspapers	Open Knowledge Foundation, Institute of Mathematics and Statistics; Jurema and Digital Ocean	Direct: 2,226 Brazilian municipalities Indirect: All Brazilian municipalities, citizens of Brazil,
CONAE	Argentina	Using satellite information to create prediction models to estimate pollution levels in Argentina, in order to create maps of the daily and monthly surface concentration of the pollutant PM10	Automate the download and preprocessing of the satellite products, and automate map processing and publishing of PM10 in interoperable formats.	CONICET postdoctoral researchers	Direct: National Commission for Space Activities (CONAE), the "Mario Gulich" Institute for Advanced Space Studies (IG, CONAE/UNC) and the Argentine Ministry of Environment and Sustainable Development (MAyDS).

					Indirect: Citizens of Argentina
Dinagua	Uruguay	Improving the control and administration of the country's water resources,	Computer vision, allowing the automation of the detection of direct extraction intakes from water bodies through the analysis of aerial images	Agência Nacional de Águas e Saneamento (ANA)	Direct: DINAGUA Indirect: Citizens of Uruguay

4.1 Types of co-production in AI in the public sector in Latin America

Understanding the geographical location, main objectives, partners, beneficiaries and type of AI tool implemented allows us to place each project in the 3 x 4 co-production typology created by Nabatchi et al (2017). Our goal is to identify and examine the differences among each project using two main variables: level of co-production and phase of the service cycle. Having this classification allows us to examine the factors and the usefulness of co-production techniques in artificial intelligence projects designed for the public good, by evaluating each project according to the classification in the typology and the reported outcomes in their financial and narrative progress reports, as well as the community calls. Table 2 shows where each project fits into the 3x 4 co-production typology.

Table 3 -3 x 4 Co-production typology in EmpatIA projects

Phase of the Service Cycle				
Level of co production	**Co-Commissioning**	**Co-Design**	**Co-Delivery**	**Co-Assessment**
Individual	**Dinagua** Dinagua worked with external consultants to create a tool that identifies water intakes in Uruguay, to improve their public water management		**ProsperIA** ProsperIA 's risk calculators are based on publicly available data from the National Health Institute and are partnering with Health Institutions to promote the use of the risk calculators	**Control Cívico** By automating the data publication, Control Cívico facilitates the assessment of public procurement in Colombia and Paraguay
Group	**CONAE** CONAE worked with doctoral students from CONICET, the Institute for Advanced Space Studies and the Argentine Ministry of Environment and Sustainable to design the algorithms to map the daily concentration of PM10 pollutant in Argentina	**Goblab UAI + SMA** The two teams worked together to produce the regression and classification models that predict the concentration of the pollutants in Chile	**IA²** Contributes to the ongoing activities of the Juzgado n° 10, making them faster and requires active engagement of the Juzgado n° 10 team, to get access to the documents and data needed	

Collective			**Querido Diario** This project scrapes data from official gazettes and publishes them in more accessible formats, which benefits the municipalities	

After examining where each project fits into the 3 x 4 typology in Table 3, we discuss the outcomes of each project organised by the phase of the service cycle in which they were created. We follow the 3 x 4 typology as presented by Nabatchi et al (2017), however, some projects might fit into more than one of the phases of the service cycle. In some cases, the projects in its original conception might fit one phase of the service cycle and one level of co-production, and change during implementation adjusting the tools for new objectives based on the resources and collaborators available. For the purposes of this paper, we focused only on the final result of each case study.

First, the co-commissioning projects: Dinagua and CONAE. Co-commissioning projects were the most disconnected from the general public, and they required high levels of thematic expertise in water and environmental management. In the case of Dinagua, we argue that this was an individual project, led exclusively by Dinagua and it became a co-production project only when they hired an external consultant to contribute to their operations, particularly for the implementation of AI tools. In the case of CONAE, their collaboration with other groups that have a similar thematic expertise facilitated the use of satellite information to map the daily concentration of the PM10 pollutant in Argentina.

The second phase of service delivery, co-design project is an in between point among co-commissioning and co-delivery. Here we identify the project led by the GobLabUAI + SMA, it is similar to the Dinagua and CONAE projects in terms of requiring high levels of thematic expertise in environmental management, however, co-producing with the GobLabUAI allowed the SMA, who already had to work on these models to improve their day to day activities, to incorporate new technologies and agile methodologies that they otherwise would not be using. This allowed both teams to consider the needs of the users, including the SMA, in the regression and classification models created in the project. This allowed the SMA to comply with their mandate and made the information more easily accessible to users in the general public.

The third phase of co-production was the most commonly represented by the participating projects: co-delivery, although the level of co-production did alter the outcomes of the projects significantly. First, at the individual level, ProsperIA. This project had the least amount of interaction with partners in the initial phases of the project. Initially, ProsperIA only used publicly available data from public institutions such as the National Nutrition and Health survey. Once they created the risk calculators and created adaptive questionnaires hosted in web platform, they started seeking collaboration opportunities with Mexican Health Institutions such as the Mexican Diabetes Federation, Hospital de Nutrición de México and the Institute of Public Health Citizenship in order to promote the use and recommendation of the services created by Prosperia. They had enough thematic and technical expertise to carry out the project by themselves, but they need collaboration with public institutions who have day to day access to the population Prosperia's project is trying to serve.

On the group level of co-production in the co-delivery phase we find the IA² project. This was envisioned as an active collaboration with the Court n° 10 of the City of Buenos Aires, and it required the active engagement of Cambá with the Juzgado n° 10 team, to get access to documents and data they needed to create the tool. These projects needed thematic expertise that was provided by the Court n° 10 of the City of Buenos Aires and technical expertise provided by Cambá Cooperative. The result of the collaboration was the improvement of the public services provided by the Court n° 10 of the City of Buenos Aires to their users and the general public. Lastly, in this category, we find the Querido Diario project. This project initiated with little contact with public institutions, and interacted mostly with the publicly available information

from the official gazette. However, they collaborated with a wide variety of institutions including academia and other civil society organisations to create the project, interestingly the Open Knowledge Foundation also works with volunteers that provided technical expertise in the development of the open source AI tool they created. Once they had the tools in place and were able to scrape the data, OKFN reports that some municipalities reached out to them to use their tools to improve the quality of their municipal gazettes.

Lastly, the co-assessment phase of the service cycle was only represented in one of the projects: Control Cívico. In this project, CDS created a Twitter bot based on the data published by the National Directorate of Public Procurement (DNCP) of Paraguay and the National Public Procurement Agency of Colombia. CDS has contributed over time to the Open Contracting Data Standard publication of both of these entities, and reports to have a very close working relationship with the DNCP and a good working relationship with Colombia. In this case, CDS has technical expertise and thematic expertise they have built over years of collaboration with both entities, which allows them to position themselves as unique experts that can contribute to the evaluation of public procurement in Colombia and Paraguay, from publication to red flag monitoring.

5. Co-production Projects in Latin America: Lessons learned

The first lesson learned is that data is an essential component of artificial intelligence co-production projects. Scrollini, Cervantes & Mariscal (2021) identify that all projects participating in Empatía use public data that relies on the state's data infrastructure. Data infrastructure are the technical means, services and facilities used where data is produced, maintained and distributed.

Ensuring the quality of data infrastructures requires a significant investment of time and effort. For example, to follow the same data standard and the constant publication and revision of the same. Given that the state is the biggest producer of public data, most co-production projects for artificial intelligence will have a dependency on state actors. If these infrastructures are not of good quality, projects related to the public sector are likely to fail.

In the case of CONAE, Dinagua and the GoblabUAI-SMA project, the project leaders were also the people in charge of maintaining the data infrastructures, which allowed them to have greater control over the production, maintenance and distribution of that data. However, this requires more investment of time, money and trained personnel, and often the quality of data infrastructures depends on maintaining the institutional memory of previous governments. This characteristic made the projects fit into the passive, individual and compliant characteristics of the Bussu & Galanti's co-production typology. In these three examples it was possible to observe different success levels in the implementation of the projects, directly related to the ability of state actors to access high quality, standardised data, which they had to produce or at least collect themselves. Dinagua reports that after the implementation of the project, they have rewritten the data collection guidelines to ensure that future data collection is easier, by standardising procedures such as the colour and size of the water intakes.

One of the main findings is the role of data standardisation in the success of projects, specifically those led by the private sector with public data, such as Control Cívico (CDS) and ProsperIA. These projects had the least interaction with the state, although they relied on the state's previous and continuous efforts of data collection and open data access. Throughout the process we found that projects that were familiar with the required data infrastructures had a significant advantage over other projects, allowing them to move faster by being able to reuse good quality public data. This was mainly the case for projects led by the private sector, which created their products based on data that had a good infrastructure over time, often in collaboration with the agencies that are in charge of them.

The next lesson learned is that co-production initiatives have the potential to contribute to innovation in the internal processes of the organisations, particularly for state actors. Jaspers and Steen (2020) argue that capacity building for sustained co-production includes institutionalising processes. According to their view, this extends beyond the provision of regulative frameworks supportive of co-production and includes the structural allocation of required resources. While formal regulations might take a long time to change, the teams reported that they have incorporated new ways of working into their regular processes after implementing their co-production projects. For example, Gob Lab and SMA's leaders told us that the ways

in which academia works is very different from the SMA's processes, but their work together made both teams improve their processes. For example, in terms of documentation and open access to the code, the Goblab team mentioned that they have the policy to document everything on Github, a policy the SMA did not have in place. After their collaboration, the SMA usually does not work with public facing documentation or code, but this experience showcased the value of doing so.

In several of the case studies, institutions had to hire outside consultants which brought external knowledge to the organisation. According to Steen & Bransen (2020) the contribution of professionals and citizen co-producers should be complementary rather than merely substitutive. Hiring external consultants is a short-term solution that can contribute to ameliorate a lack of internal expertise. This might work for short term projects, although the specific technical knowledge brought on by the consultant will stop when the consultancy ends, unless knowledge sharing mechanisms, such as trainings, are put in place.

A fourth lesson is that co-production projects that use public data and only have a transactional relationship with the state are less likely to become long term or permanent collaborations. However, co-production seems to be an adequate solution to the lack of technical expertise in artificial intelligence in the public sector, and the inability of the public sector to compete with the market value of technology experts as it currently stands. The risk of outsourcing innovative projects after the initial co-production initiatives is that there is a reduced likelihood of long term implementation of these projects, as they would require constant streams of external funding, which often relies on the availability of grants and funds from international organisations.

5. Concluding remarks

In this paper, we seek to explore how different stakeholders co-produce AI solutions in government. To do so, although limited to 7 cases in Latin America, we analyse these cases using the framework produced by Nabatchi et al (2017). We not only classify them, but also highlight those lessons learned from the way different actors collaborate among each other. We find four main lessons of co-production techniques to artificial intelligence for the public good projects. First, there is a transfer of technical skills from the private sector and civil society to the public sector that would be too costly and unsustainable without established mechanisms in which state actors and other actors work together to produce benefits for the public good. Second, that partnerships are diverse and to some degree unique and could involve small firms, cooperatives, or civil society organisations according to context and objectives.Co-production allows AI to leave the exclusive realm of big firms and co-production mechanisms could help to diversify a highly concentrated market. Future research could focus on other regions of the world, or longer experiments in co-production for the public sector.

In line with the previous findings, the public sector contributes with thematic expertise and access to public data that private entities would otherwise not have on their own. And lastly, the framing of co-production projects as "projects for the public good" by funding entities contributes to incorporating the logic of openness, particularly in using open source and open data, that individual actors, public or private, might not use otherwise. In this way AI tools can be developed in a transparent, verifiable and potentially scalable way.

References

Ehsan, U., Singh, R., Metcalf, J., & Riedl, M. 2022. "The Algorithmic Imprint". In *2022 ACM Conference on Fairness, Accountability, and Transparency*. pp. 1305-1317).

Howlett, M., Kekez, A., & Poocharoen, O. O. 2017. "Understanding co-production as a policy tool: Integrating new public governance and comparative policy theory". *Journal of Comparative Policy Analysis: Research and Practice*, (19:5), pp.487-501.

Kang, S., & Van Ryzin, G. G. 2019 "Coproduction and trust in government: evidence from survey experiments". *Public Management Review* (21:11),pp. 1646-1664.

Kuziemski, M., & Misuraca, G. 2020. "AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings". *Telecommunications Policy*, (44:6).

Mergel, I. 2015. Opening government: Designing open innovation processes to collaborate with external problem solvers. *Social Science Computer Review*, (*33*:5), pp.599-612.

Misuraca, G., van Noordt, C., & Boukli, A. 2020. "The use of AI in public services: results from a preliminary mapping across the EU". In *Proceedings of the 13th International Conference on Theory and Practice of Electronic Governance* (pp. 90-99).

Nabatchi, T., Sancino, A., & Sicilia, M. 2017. "Varieties of participation in public services: The who, when, and what of coproduction". Public Administration Review, (77:5), pp.766-776.

Ostrom, E., Parks, R. B., Whitaker, G. P., & Percy, S. L. 1978. "The public service production process: a framework for analyzing police services". *Policy Studies Journal*, 7, pp. 381.

Prudencio, K. 2021. *Estrategias de Inteligencia Artificial en América Latina*. ILDA. Montevideo.

Scrollini, F, Cervantes, M & Mariscal, J. 2021. *En busca de rumbo: el estado de las políticas de inteligencia artificial en América Latina*. ILDA. Montevideo.

Smith, M., & Neupane, S. 2018. *Artificial intelligence and human development: toward a research agenda*. IRCC. Canada.

Whitaker, G. P. 1980. "Coproduction: Citizen participation in service delivery". *Public Administration Review*, pp. 240-246.

Wu, D., Verhulst, S., Pentland, A., Avila, T., Finch, K., & Gupta, A. 2021. "How data governance technologies can democratize data sharing for community well-being". *Data & Policy*, *3*.