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RPR REVIEW OF POLICY RESEARCH

Policy capacity and rise of data-based policy innovation labs

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Abstract

In scarcely a decade, a "labification" phenomenon has taken hold globally. The search for innovative policy solutions for social problems is embedded within scientific experimental-like structures often referred to as policy innovation labs (PILs). With the rapid technological changes (e.g., big data, artificial intelligence), data-based PILs have emerged. Despite the growing importance of these PILs in the policy process, very little is known about them and how they contribute to policy outcomes. This study analyzes 133 data-based PILs and examines their contribution to policy capacity. We adopt policy capacity framework to investigate how data-based PILs contribute to enhancing analytical, organization, and political policy capacity. Many data-based PILs are located in Western Europe and North America, initiated by governments, and employ multi-domain administrative data with advanced technologies. Our analysis finds that data-based PILs enhance analytical and operational policy capacity at the individual, organizational and systemic levels but do little to enhance political capacity. It is this deficit that we suggest possible strategies for data-based PILs.

KEYWORDS

data, fourth industrial revolution, policy capacity, policy innovation labs, policy theory

INTRODUCTION

In the public policy arena, a "labification" phenomenon—or the search for innovative policy solutions for social problems through scientific experimental-like structures—has taken hold on a global scale. Policy labs, also referred to as policy innovation labs (PILs), seek to address pressing social or economic issues and can be found within government agencies, universities or not-for-profit organizations. In global terms, most PILs have been established since 2011, and their rapid growth has led to claims that they "are on the path to becoming a pervasive part of the social infrastructure of modern public organizations" (Carstensen & Bason, 2012, p. 5). Policy labs share similarities and resemble well-known organizations, including think tanks, research institutes, or policy shops with their shared goals of providing policy solutions for problems that often arise in specific sectoral areas such as health, welfare, open or big data, and the environment.

Despite the growth, the policy lab literature focuses on descriptive accounts of their activities and the tools and techniques that are employed. Yet, important questions remain as to whether PILs are enhancing our ability to understand and address critical policy problems. To help address this question, we examine on how PILs contribute to policy capacity by focusing on one type of PIL—data-based policy innovations labs, which employ new technological advances in data availability and access as well as cutting-edge data analytic processes. In general, we would expect data-based PILs to enhance policy capacity, but how and in what ways they are currently supporting policy capacity has not been documented. In this study, we map out how data PILs contribute to the nine possible types of policy capacity described by Wu et al. (2018).

To ground our study, we first offer an overview of the policy capacity literature. We then discuss the growing global labification trend that has been underway for nearly a decade, followed by the limited literature on data-based PILs. We then review 133 data-based PILs located across the world and provide a descriptive account of such factors as their size, location, and autonomy. In our review of PIL policy capacity, using Wu et al.'s (2018) taxonomy, generally missing from PILs is political-based policy capacity at the individual, organizational, and systemic levels. To offer avenues for these labs to enhance their political capacity, we draw upon the policy process literature. We conclude by discussing the theoretical and empirical lessons from this research and offer a research agenda for understanding how different forms of policy capacity can support processes of policy learning and innovation.

ADOPTING A POLICY CAPACITY APPROACH

Wu et al. (2018) argue that policy capacity is among the most fundamental concepts in studying public policy due to its connection to superior policy outputs. The rich policy capacity literature provides several definitions of policy capacity. Honadle (1981) defines it broadly as "the ability to anticipate and influence change; make informed, intelligent decisions about policy; develop programs to implement policy; attract and absorb resources; manage resources; and evaluate current activities to guide future action" (p. 578). Other definitions are more concerned with the ability to respond to change (Weiss, 1998), the intellectual and organizational resources of the state (Cummings & Nørgaard, 2004), the level of knowledge management and organizational learning (Parsons, 2004), or with effectiveness of policy formulation (Goetz & Wollmann, 2001). Understanding policy capacity is particularly important when making evidence-based decision-making decisions and devising a policy or program that aligns with its original goals (Newman et al., 2017).

As policy capacity varies in a wide range of distinct steps and aspects, the concept has become more refined and is illustrated through multiple levels, skills, and competencies. Over the past -5 years, researchers have made concerted efforts to bring together the various ideas about policy capacity into a single conceptual framework. This framework, developed by Wu et al. (2018), identifies three types of skills and resources: analytical, operational, and political, which are found at three levels, namely individual, organizational, and systemic (Table 1). In doing so, the framework enables diagnoses of policy capacity from a 3 × 3 multi-dimensional perspectives.

Analytical policy capacity contributes to the technical articulation of policies (Wu et al., 2015). Policy capacity at the operational level helps align resources with policy actors for effective implementation in practice. Political capacity allows the acquisition and sustaining of political support for policy implementation. Political support is crucial because agencies or organizations must be legitimate for citizens and policy targets to receive the necessary resources and support for policy actions (Painter & Pierre, 2005; Wu et al., 2015).

Concerning resources and capabilities, the individual level comprises policy actors, including policy makers, public officials, and experts with a key role in policy processes. The individual's policy capacity is associated with their knowledge, skills, and expertise about policy itself, policy processes, and political judgment (Wu et al., 2015). Policy capacity at the individual level requires policy capacity both at organizational and system levels to ensure the effectiveness of a policy. Policy capacity at the organizational level includes systems managing human and financial resources, available information and knowledge, and political support. Organizational policy capacity can enhance or undermine individual capacity. Policy capacity at the systemic level involves economic, social, and security systems in which policy processes operate, and the level of trust and support the society and the community provide to an organization or an agency (Wu et al., 2015).

The steadily increasing importance of policy capacity has spurred applications of the policy capacity framework. Studies have adopted the concept of policy capacity to identify their general strengths and weaknesses of policy sectors or government jurisdictions (Wu et al., 2015). The policy capacity framework allows for identifying policy capacity with more sophisticated and systematic comparison and analysis (Tenbensel & Silwal, 2022). Empirical studies have applied the policy capacity framework in diverse contexts, including the health governance system (e.g., Bali & Ramesh, 2021; Lawrence et al., 2020; Tenbensel & Silwal, 2022), policy capacity in response to COVID-19 (e.g., Capano et al., 2020; Wong, 2021; Woo, 2020), consultancy in public administration (e.g., Althaus et al., 2021), and biodiversity in the economy (e.g., Förster

TABLE 1 Policy capacity framework

Levels of resources and capabilities	Skills and competencies		
	Analytical	**Operational**	**Political**
Individual	Individual analytical capacity	Individual operational capacity	Individual political capacity
Organizational	Organizational analytical capacity	Organizational operational capacity	Organizational political capacity
Systemic	Systemic analytical capacity	Systemic operational capacity	Systemic political policy capacity

Note: From Wu et al. (2018).

et al., 2021). As such, the policy capacity framework allows for investigating how governance systems or institutions possess the overall policy capacity to achieve desirable policy outputs and outcomes in a systematic way. Given the increasing importance of PILs in policy processes, this study investigates how PILs, particularly data-based PILs, contribute to extending policy capacity to achieve desirable policy outcomes. This study applies the policy capacity framework of Wu et al. (2018) to investigate the contribution of data-based PILs to enhance policy capacity in a systematic analytical way.

THE RISE OF POLICY INNOVATION LABS

The recent growth in PILs raises questions about their contributions to different forms of policy capacity. To date, however, scholars have paid limited attention to their policy capacity. We do, however, from a growing PIL literature, know that policy labs are designed in diverse ways. For instance, the term "policy lab" can include established teams (or organizations, or institutes) set up specifically for innovative activities for public policy making and physical spaces set up to conduct workshops or other stakeholder activities. Muddying the picture is also the growth of other related organizations such as living labs, research institutes, and nudge (behavioral economics) groups contributing to policy making. Wellstead and Howlett (2021) referred to this confluence as knowledge-based policy influence organizations (KBPIOs). We estimate that there are well over 450 lab-like entities worldwide. This number was corroborated by Villa Alvarez et al.'s (2022) worldwide survey of PILs.

Despite this ambiguity, PILs tend to share three distinctive features. First, PILs use of design-thinking methodology (e.g., Lee & Ma, 2020; McGann et al., 2018), which originated in industrial and product and service design (Manzini, 2015). Second, they focus on innovation through the application of experimental approaches and the emulation of scientific methodologies to test and measure the efficacy of various public policies and programs, thus drawing on experiments, often as pilots or prototypes. By seeking to emulate scientific methodologies, PILs attempt to evaluate and measure the efficacy of various public policies and programs as well as to provide evidence for evidence-based design (Bason, 2017; Kimbell, 2015; Lee & Ma, 2020). Third, PILs have a user-centric approach whereby target populations actively engage in the design process (Lee & Ma, 2020). Indeed, many PILs coordinate efforts between public, private, and academic actors (Williamson, 2015). Additionally, PILs typically use a wide range of digital instruments to allow public transparency (Olejniczak et al., 2020). Therefore, an important goal of PILs is to create a collaborative space to enable participants with varied skill sets to reach a common understanding of a policy challenge and then explore, design, and test user-centered solutions for potential implementation across the system (Bellefontaine, 2012; El-Haddadeh et al., 2014). Thus, PILs are both a process and a particular kind of workspace that breaks down hierarchies and engages people in divergent and creative thinking (Gryszkiewicz et al., 2016; McGann et al., 2018).

Guided by user-centric approaches and drawing on experiments as pilots, PILs aim to address the well-documented phenomena of implementation gaps (e.g., Gassner & Gofen, 2018) and noncompliance (Gofen, 2015) by enhancing the notion of evidence-based design. The policy labification trend supports Lindquist and Buttazzoni's (2021) argument that these widely different manifestations often recruit knowledge and skills from other parts of an organization or related organizations. The PIL approach further encourages flexibility, adaptation, and creativity to deal with environments characterized by uncertainty and ambiguity, produce innovative products, and build emergent strategies (Lindquist & Buttazzoni, 2021).

DATA-BASED POLICY INNOVATION LABS

Understanding the types and approaches of policy labs is vital when considering their roles in policy processes (McGann et al., 2017). Among diverse characteristics that consist of policy labs, data are core components in diverse types of PILs as they provide technological expertise in data science and digital analytic methods (Lee & Ma, 2020; Williamson, 2015). In addition, new technologies are allowing government agencies, universities, and nonprofits to engage with diverse sources of data, which is driving the emergence of data-based PILs that work to improve the design of policies and their outcomes.

Data-based PILs facilitate social responses to rapidly changing and developing technology that enables decision-makers to benefit from new data sources (Janssen et al., 2012). The terminology of a "fourth industrial revolution" increasingly arises in the policy domain, and advanced technologies and the digital revolution are clearly having an impact on public policy and governance (Schwab, 2017; Wellstead et al., 2022). With the growing importance of technology and data, data-based PILs have emerged to facilitate "data-based decision-making." This relates to the concept of evidence-based decision-making, (McGann et al., 2017), while focusing on data sources (van Veenstra & Kotterink, 2017). As technology rapidly develops, government agencies are collecting enormous amounts of data on an unprecedented scale—and these "big data" are used to tackle pressing public problems. Such technology can make policy-making process more efficient and responsive than evidence-based policy making that relies on stakeholder engagement alone (Wellstead et al., 2021). In addition, data-based PILs with data-driven decision-making are including citizens to co-create user-friendly policies and products. Citizen engagement in working with data-based PILs to co-design is increasingly important for supporting open-source data analysis.

Data-based PILs work to improve citizens' experiences of public services, using diverse data sources, advanced technology, and innovative solutions. They highlight the importance of data as information and use advanced technologies to maximize its value (Bannister & Connolly, 2014; Kim et al., 2014). Government agencies create or collaborate with data-based PILs to make effective use of a variety of data sources and digital technologies. The growing demand for advanced digital technology and data-analysis methods is helping government agencies develop their administrative processes, including their performance measures and procurement processes; to understand the data concerning the movement of people and goods; and to capture data gaps. The data-analysis methods employed by government agencies align with multiple advance technologies, including algorithmic tools that can analyze data at an unprecedented scale and use technologies such as artificial intelligence (AI), robotics, the "Internet of Things" (IoT), augmented reality, and biotechnology. Data-based PILs often use machine learning technology to manage increasing volumes of data, thereby enabling them to improve the delivery of public policy and public services. For example, data-based PILs, such as the Smart City Living Lab in Germany, employ AI technology to predict patterns and identify unusual conditions or anomalies that can impact real-time data systems. Despite their increasing importance, there is a dearth of research on data-based PILs describing their foci, the technologies they use, and whether they produce or enhance policy capacity. We fill that gap by first describing the extent, location, and functions of data-based PILs. We then unpack how they contribute to various types of policy capacity, as introduced above.

REVIEW OF THE DATA-BASED POLICY INNOVATION LABS

There is no consensus what exactly defines policy innovation lab. They can "range from established teams (or organizations or institutes) set up specifically for innovative activities for public policymaking, to physical spaces set up for the purpose of conducting workshops or activities for policymaking" (Hinrichs-Krapels et al., 2020, p. 2). Tõnurist et al. (2017) argue that they were created to cope with technology-induced demands on the public sector, as a response to external complexity, to support internal learning, and legitimize change through specialization and the concentration of experts. McGann et al. (2018) provide a similar explanation for their growing popularity. Recent studies have cataloged the global growth of policy labs (Gofen & Golan, 2021; OECD, 2017; Villa Alvarez et al., 2022; Wellstead & Nguyen, 2020). These efforts take three broad criteria into account, namely policy labs are engaged in the public policy process or public sector reform and that they are unique spaces dedicated innovative activities. We found a great deal of consistency between these databases. Based on these catalogs, in January 2022, we searched for policy labs engaged in "data" related to the fourth industrial revolution technologies described above. From over possible 400 policy labs, 133 met these criteria. The list was validated through additional desk research. Data-based PILs that were terminated or were not associated with an operative website or had any official documents were removed.

Most of the data-based PILs' websites contained detailed official documents, reports, blogs, press releases, and articles that formed the basis of the document coding for the descriptive overview. The analysis was conducted using exploratory coding and involved the following iterative procedures: (1) a review of all the data-based PILs; (2) the creation of categories; (3) a review of all data-based PILs based on the categories; (4) the creation of themes in each category; and (5) an investigation of the websites and relevant documents, with coding of the themes under each category. We conducted both quantitative and qualitative analyses using the coding categories and exploratory comparative analysis.

Table 2 presents the geographic location for data-based PILs. Most data-based PILs operate in the United States (43.6%) or Europe (30.8%). Most focus on services within the regions in which they are located, while the OECD and UNICEF provide services transnationally.

Governments initiated 43.6% of labs. Over a quarter (27.1%) are operated by universities, which reflects the importance of data-driven policy making and research on diverse types of data and technologies (Table 3). Nonprofits (13.5%) and social enterprises (2.3%) account for 15.8% of the labs. The lab coded as "Others-mixed" is the Digital Social Innovation Lab in Germany, initiated by a collaboration of the University of Mannheim with Social Entrepreneurship BW, with the support of a corporate entity.

Labs operated by government departments or agencies were found at different levels (national, province/state, and municipal). Of the 58 government-based labs identified in this category (see Table 4), 39.7% operate at the national level and 44.8% at the municipal level. Seven labs at the municipal level in the United States were launched by and partnered with "What Works Cities" from Bloomberg Philanthropies.

Type of data

We identified the type of data that data-based PILs examine (Table 5). Not surprisingly, since improving public innovation and digitalized services are often key goals, lab administrative data

TABLE 2 Geographic location of data-based PILs

Geographic location	Number	Percentage
Region where the policy lab is located		
United States	58	43.6
European countries	41	30.8
Australia and New Zealand	10	7.5
South America	10	7.5
Asian countries	5	3.8
African countries	3	2.3
Canada	2	1.5
Middle eastern countries	2	1.5
Transnational	2	1.5
Sum	133	100

TABLE 3 Type of data-based PIL entity

Type of policy lab entity	Number	Percentage
Type of entity under which the policy lab is formed		
Government	58	43.6
University	36	27.1
Non-profit	18	13.5
Business	8	6.0
Research institute	6	4.5
Social enterprise	3	2.3
International organization	3	2.3
Others-mixed	1	0.7
Sum	133	100

TABLE 4 Government level of data-based PILs

Government level	Number	Percentage
Level of government at which the policy lab is located		
Municipal	26	44.8
National	23	39.7
Province/State	9	15.5
Sum	58	100

are employed in 27.1% of the case and 18.8% of labs employed mixed types of data. For example, MIT BigData Living Lab develops systems with technologies that employ “small data,” that is, personal data collected by smart phones, new wearable sensors, and tracking devices, and big data, including Wi-Fi data, social media data, city data, transportation data, and weather data.

Labs more focused on advanced technologies, without specific descriptions of data, are coded in the category of others (unspecified), which includes 18.8% of labs. In addition, partner/

TABLE 5 Type of data used by data-based PILs

Type of data	Number	Percentage
Type of data that the policy lab uses		
Administrative data	36	27.1
Mixed type	25	18.8
Others [unspecified]	25	18.8
Own collected research data	12	9.0
Client data	9	6.8
Health data	9	6.8
Partner/Collaborator data	8	6.0
Urban/Transport data	8	6.0
Geographic forestry data	1	0.7
Sum	133	100

collaborator data were used in 6% of the labs, highlighting the collaboration between technology experts and policy makers. The labs (6.8%) that make a profit and are associated with technology and data experts were described as using "client data," including diverse topics and data types.

Health data are also key for data-based labs focusing on health digitization and health innovation, which account for 6.8% of the total. The Institute for Innovation + Improvement in New Zealand adopts new technologies and data systems to identify patients' outcomes and experiences, to enable clinicians track the data, and thus to improve the efficiency and effectiveness of patient care. PATH Uganda employs health data for digital health transformation in which clinicians provide efficient healthcare with digitalized data sources.

Policy domain

We also categorized the policy areas targeted by the data-based PILs. As the labs focus on data, advanced technology, and digitalization, the majority (60.2%) relate to multiple policy domains (Table 6). The labs (10.5%) focusing on digital science, digitalization, and the development of advanced technologies—and not covering specific policy domains—were coded as "Digitalization/ digital science."

TECHNOLOGIES UTILIZED BY DATA-BASED POLICY INNOVATION LABS

As powerful computers have become less expensive, more availability for computing and digital technology has introduced some of the largest transformations of the past half century (Alpaydin, 2021). The computer is not only a data-storing and processing machine; it has also become a means of transferring and sharing data and information with computer networks. Due to this increased connectivity among computer networks, digital transferring and digital communication become fast, reliable, and available to anyone, anywhere. Our analysis found that data-based PILs develop and use multiple types of technologies that focus on digitalization by dealing with broader advanced technologies, rather than specific types. While the labs use a variety of

TABLE 6 Policy domain of data-based PILs

Policy domain	Number	Percentage
Policy area on which the policy lab is focused		
Multi-domain	80	60.2
Digitalization/Digital science	14	10.5
Other [unspecified]	11	8.3
Health care	10	7.5
Urban/Transportation	9	6.8
Democratic governance and legislation	3	2.3
Environmental sustainability/Climate change	3	2.3
Energy	1	0.7
Defense security	1	0.7
Children	1	0.7
Sum	133	100

advanced technologies, we found some common themes, namely the role of algorithms, AI, machine learning, and IoT. We describe these representative advanced technologies and examples from our analysis in more detail below.

Algorithms, which are the core of advanced technologies, are "computational sets of rules" that programming developers design to generate patterns of decision-making (Wellstead et al., 2021). Simply put, an algorithm refers to a sequence of instructions regarding how to transform the input to the output (Alpaydin, 2021). The increasing availability of data, the use of big data, and the necessity of models have led to the increasing importance of algorithms for rapidly performing more detailed autonomous tasks among diverse fields (Dwivedi et al., 2021). Some data-based PILs develop algorithms to facilitate more efficient and digitally optimized services and systems. A variety of algorithms are designed and used for processing of digitally collected data from diverse areas of citizens' daily activities. For example, Health High Density Cities Lab in Hong Kong develops new algorithms in urban design to find optimization for walking and landscaping. The Behavioral Insights Team in the United Kingdom provides data science and analysis to find patterns in data using computer algorithms and machine learning to improve public services. The Immigration Policy Lab, a research group from Stanford University and ETH Zurich, develops algorithms detecting hate speech to find counter speech strategies in immigration and refugee issues. Furthermore, data-based PILs support the general understanding of algorithms. For instance, Toi Āria in New Zealand suggests strategies for improving levels of comfort in algorithmic decision-making with improved transparency and communication, based on the findings that distrust in the current system contributes to communities' low comfort with algorithmic decision-making.

Machine learning, algorithms, and AI are employed in the optimization of services and products. With machine learning, data are no longer passive but can define what to do next without the need for programmers (Alpaydin, 2021). Machine learning helps to modify mistakes and prohibit the same mistakes in a system with a changing environment. Machine learning technologies are also developed and adopted in the public sector and bring implications for all aspects of government actions (Eggers et al., 2017). Data-based PILs have employed machine learning technology to pursue optimization of public services and products. For example, Nesta in the United Kingdom employs machine learning technology to obtain a better understanding of the future labor market and to better inform on career advice. Rhode Island Innovative Policy Lab in the United States uses the state's data and machine learning and AI techniques to provide job seekers with optimal career information on in-demand careers, job training, and reskilling suggestions. Algorithms analyze job seekers' skills and experience from their resume and suggest types of new careers based on the state's labor data.

Artificial Intelligence (AI) is related to algorithms and machine learning. AI technologies include machine learning, natural language processing, robotics, and other algorithmic technologies (Dwivedi et al., 2021), which are advanced technologies involving prediction (Agrawal et al., 2017). AI technologies detect patterns from big data and provide predictions for cases from new yet similar data (Dwivedi et al., 2021). The core concept of AI involves programming non-human intelligence for specific tasks (Dwivedi et al., 2021). For instance, intelligence can be located at the sensors for effective reaction times or protecting privacy-sensitive data, or it can be in the data center systems. AI enables the facilitation of new practical applications in diverse dimensions, including management, healthcare, finance, transportation, and education, with increasing performance that efficiently and rapidly extends beyond the human domains (Daugherty & Wilson, 2018; Miller, 2018). As such, data-based PILs use AI technologies to build better management of the public and private sectors and enhance community living environments. Smart City Living Lab in Germany develops and tests innovative information and communication technologies and AI for the development of urban living environment. ATC (Athens Technology Center) Innovation Lab in Greece tests services using a broad range of technologies, including AI, and promotes the integration of AI technologies to improve manufacturing systems.

Governments have developed and tested AI-based algorithms to pursue efficiency in public services (Janssen & Kuk, 2016). For example, AI systems have led to the development of chatbot services in public sectors, autonomous vehicles, autonomous planning, translation, and medical services, based on collected big data and machine intelligence (Dwivedi et al., 2021). New York City (NYC) Mayor's Office of the Chief Technology Officer supports the NYC AI Strategy, which is a foundational initiative for a cross-sector AI ecosystem in NYC. Many data-based PILs support better shared understanding of advanced technologies, including AI, and analyze related challenges and opportunities. Global Pulse Lab Kampala in Uganda promotes the adoption of AI technologies, explores new AI applications for sustainable development, and guides the responsible use of big data and AI. Other data-based PILs, such as GobLab UAI's effort, build capacities for ethical data management and ethical standards for algorithmic decision-making and artificial intelligence.

The Internet of Things (IoT) represents networks of physical devices that communicate with embedded sensors and software over the internet. It is possible to track the movement of objects by connecting physical and digital devices and objects with increased connectivity (Greengard, 2021). The IoT system provides a data-sharing network that does not require human intervention, such as interactions between humans or between a human and devices (Sulaiman et al., 2021). Home automation gear, media players, smart watches, and surveillance cameras serve as examples of the IoT found in our daily lives. The interacting devices share data through the internet, with minimal human intervention, which enables efficient, hyperconnected societies that connect the physical and the digital. The IoT enables connection between objects and supports communication between people, processes, and things. Montreal Urban Innovation Lab tests the IoT for better management of the city and optimization of citizen movement for smart cities and analyzes the social acceptability of these technologies. Kansas City Living Lab in the United States contributes to building Kansas City as a smart city based on IoT technologies partnered with the private sectors, such as Cisco and Sprint.

iiLab in Portugal contributes to technological development and research, technology transfer projects, and advanced consulting and training for the academic, public, and private sectors. iiLab has researched how to design, manufacture, and implement IoT technologies. The lab is working on how to resolve the challenges of these technologies, such as efficient management of the vast amounts of data available and processed, cybersecurity, privacy, and other issues that the IoT-related technologies raise in the continuous technological innovation and evolution cycle.

The availability of big data accompanies the evolution of the IoT (Janssen et al., 2015) and big data lead to added intelligence in algorithms to process these big data (Dwivedi et al., 2021). Data-based labs explore new applications of big data, AI, and the IoT to provide innovative social solutions. Some data-based labs employ and develop diverse types of technology for innovative solutions, and others work as hubs connecting differing experts in specific technologies. For example, Digital Hub Initiative in Germany connects networks of experts in AI, IoT, FinTech, mobility, smart infrastructure, digital health, cybersecurity, and future industries with new technology.

Overall, data-based PILs use technologies of algorithms, AI, machine learning, and the IoT to help citizens in their daily lives by developing public products and services to be specialized for service users. The use of such technologies enables data-based PILs and public agencies to collect public patterns and make correct predictions for the future and provide solutions efficiently and correctly to address public problems in a rapidly changing society.

CONTRIBUTION OF DATA-BASED PILS TO POLICY CAPACITY

Well-developed policy capacity can support desirable policy outcomes. It is important to not only identify whether and where policy capacity exists, but what mechanisms can strengthen or enhance existing capacity. This section presents how data-based PILs contribute to the nine types of policy capacity described in Table 1. Here we provide selected examples of policy capacity from the 133 identified labs as well as the outcomes. Table 7 outlines the broad indicators that guided our review.

Individual analytical capacity

Individual analytical capacity matters for evidence-based policy making and public innovation, where public officers can absorb data and information for every stage of a policy process (Wu et al., 2015). The analytical capacity of individuals involves diagnosing policy problems and formulating the appropriate plans and strategies to address these problems (Wu et al., 2018). Individual analytical capacity is required to properly think about policy design, which can be misguided if there is a lack of individual analytical capacity or understanding of capacity. To achieve efficient modification and implementation of policies, governments require employees to develop analytical skills. This study found data-based PILs contribute to enhancing individual analytical capacity by providing educational training and fellowships for public officials and citizens.

Data-based PILs highlight that public officers must learn and adapt to digitalization in administration. Some provide fellowship programs for government agencies and public officers to help them learn advanced technologies and digital transformation processes. Data-based PILs

TABLE 7 Summary of data-based policy capacity

Levels of resources and capabilities	Skills and competencies		
	Analytical	**Operational**	**Political**
Individual	Development of design thinking and other approaches	Leadership and coordination within labs	Understanding of policy labs in the policy process (policy cycle) Negotiation and consensus building skills
Organizational	Availability of data analysis and tools across an organization. Developing processes for collecting and analyzing data	Designing tools within governmental and non-governmental agencies Information technology to improve integration and coordination Degree of policy lab autonomy Communication with stakeholders and the public	Stakeholder engagement, legitimacy of the process Policy learning
Systemic	Data analysis and tools across society Political buy in for analysis and tools Link to advisory systems Agenda setting	Building policy networks Facilitating policy implementation	Trust building Opportunities for people to engage as policy actors Contributing to the infrastructure of policy subsystems

support individuals to build analytical capacity by helping them to think about innovative approaches and formulate appropriate plans using technologies. Individuals' understanding and consideration of innovative approaches and solutions with the use of technologies are strengthened through the support of data-based PILs. For example, Code for Australia has run the program, "Tech For Non Tech," which helps non-technical individuals to develop their capabilities by deepening their understanding of technical and web development. Waag in the Netherlands provides educational courses for leaders, professionals, teachers, and individuals on applying technology and designing innovative solutions through its Waag Academy programs. Our analysis suggests that some data-based PILs support the enhancement of individual analytical capacity by allowing individuals to think about innovative approaches and design solutions with the use of technologies to address policy problems.

Organizational analytical capacity

Public agencies and organizations should possess organizational analytical capacity, which includes efficient systems for information collection and dissemination within and across agencies. Such information management systems are critical in evidence-based decision-making, which requires information, knowledge, and data to be analyzed and available in a timely and systemic ways (Davies et al., 2000; Wu et al., 2015). Organizational analytical capacity primarily includes machinery and processes in collecting and analyzing data and the extent of organizational commitment in pursuing evidence-based policy (Wu et al., 2018). Previous studies have suggested that cross-boundary data information integration is necessary for successful use of new data sources in public services (Gil-Garcia & Sayogo, 2016), but also find challenges in data sharing across agencies due to a lack of standardization (Gil-Garcia & Sayogo, 2016; Janssen et al., 2012). Data-based PILs can enable digital transformation processes in government agencies, primarily from an administrative paper-based form and manual process to a digitalized form and process, to minimize complexities in public services and create a more efficient system of collecting and analyzing data. For example, the Innovation Team (i-team) at the City of Syracuse's Office of Accountability improved the previous inefficient process dealing with various types of data by transitioning the process from paper to digital.

Our analysis indicates that most data-based PILs under governments or collaborating with governments contribute to developing standardized and digitalized processes that expand upon organizational analytical capacity. We found that data-based PILs have developed programs to standardize processes across and within government agencies to facilitate efficient and accurate administration. Data-based PILs provide government agencies and organizations with guidance on creating tools and methods for coherent digitalized administrative processes. They develop uniform information technology standards, as uniform processes enable governmental agencies to work more efficiently and collaboratively. For example, IT Planning Council Germany promotes uniform information technology (IT) standards and coordinates digitization of the administration. In this regard, data-based PILs strengthen organizational analytical capacity by supporting the development of a digitalized process for collecting and analyzing data to produce evidence-based policy.

Systemic analytical capacity

Systemic analytical capacity is “the general state of scientific, statistical, and educational facilities in a society which allows policy makers and workers to access high quality information to carry on their analytical and managerial functions” (Wu et al., 2015, p. 169). The extent of system-wide data collection, the availability, and the accessibility of data and information across different stakeholders can determine systemic analytical capacity (Wu et al., 2018). We found that data-based PILs often manage open systems for government data to promote innovative and data-driven policy making (Wellstead et al., 2021). New digital technologies and web-based data-analytics tools are employed to manage public data on government agencies' websites to increase diverse stakeholders' accessibility (McGann et al., 2018). Data-based PILs with or within governments have an essential role in managing public data and allowing accessibility to data for private organizations, researchers, non-profit organizations, and the public. Data-based PILs encourage open government policies and coordinate the processes of public data management, thereby increasing the level of system-wide data accessibility. For example, Louisville Office of Civic Innovation contributes to enhancing systemic analytical capacity by opening and managing data on budget, crime, health, salaries, and emergency management, which are likewise used by private or nonprofit sectors and citizens.

In addition, education on the implementation of public policy and the technologies used in a society can improve systemic analytical capacity, which also enhances organizational capacity for effective performance. The promotion of digital equity and the availability of data at the system level is a primary outcome of the data-based PILs that promote digital civil society and digital skills for all, which in turn enhance systemic analytical capacity. Such labs provide training and workshops for citizens. For example, the Code for Pakistan Civic Innovation Lab in Pakistan runs an outreach campaign for junior female software designers and developers. Rapid changes in digital society due to advances in technology create the risk of digital inequality, with marginalized people struggling to access the internet and other technologies. The data-based PILs promote equitable digitalization to ensure that the public can enjoy the benefits of digitalization and avoid digital exclusion. In this regard, data-based PILs support the enhancement of systematic analytical capacity by promoting equitable digitalization and producing an environment with availability of data, accessibility to data, and technologies at the system level.

Individual operational capacity

Individual operational capacity includes the capacity or ability of individual managers to implement key managerial functions, including policy designs, managing human and financial resources, direction, and coordination (Wu et al., 2015, 2018). Individual operational capacity is particularly important for formulating and implementing policies (Howlett & Walker, 2012). The Lab at the U.S. Office of Personnel Management (OPM) develops and provides design education sessions and teaches skills and the application of design concepts to individuals and teams, including federal employees. The support of data-based PILs for individual operational capacity is important because it allows managerial and leadership roles such as planning, budgeting, staffing, directing, delegating, and coordinating (Wu et al., 2018). Officials with skills and capabilities to lead and manage the use of resources and coordination are instrumental to developing and implementing successful policies (Howlett & Walker, 2012; Howlett & Wellstead, 2011). Data-based PILs can provide educational sessions or fellowship programs to aid in the development of skills for policy planning and coordination by supporting individual operational capacity. For example, the Louisville Office of Civic Innovation's Data Officer fosters collaboration among city department employees. As data-based PILs focus on the use of data and technology, enhancing individual operational capacity is often is relegated to enhancing higher levels of organization operational capacity discussed below.

Organizational operational capacity

The organizational operational capacity of public agencies or organizations influence how well organization and its officials perform. An agency's relationship with diverse institutions, including legislative and executive institutions and multiple policy actors, is important for enhancing organizational operational capacity (Wu et al., 2015). Organizational operational capacity is centered on the effectiveness of an organization, including efficient and effective performance management and coordination of resources to achieve goals (Wu et al., 2018). The level of organizational commitment for achieving policy goals is also critical in operational capacity.

As governments pursue digital transformation and user-centered design of public services for better user experiences, data-based PILs support public agencies and organizations in enhancing organizational operational capacity through innovative and technological tools and services. The design and development of user-centric products and services are key outcomes of data-based PILs. Data-based PILs redesign public services for better user-centered experiences with new technologies. Data-based PILs also adopt new technologies and data systems to identify what matters most to service receivers and improve citizens' experiences and policy outcomes. Government agencies and organizations develop innovative technological solutions to address community challenges, such as building user-centered software programs or services with the support of data-based PILs. User-friendly websites and applications for public services are developed by technology experts in the labs. For instance, the Innovation Office in San Francisco's Human Services Agency employs text message nudges to providers of home care services to attend sessions for the In-Home Support Services (IHSS) program. The Behavioural Insights Team in the United Kingdom has also highlighted the effectiveness of text reminders to achieve desirable policy outcomes. Those products and services provided with the support of data-based PILs increase the efficiency of government agencies' performance and their ability to produce effective policy outcomes.

In transportation and smart cities, data and advanced technologies enable cities and government agencies to accelerate the development of citizens' user experiences in transportation and movement. Governments and organizations also set performance management strategies and develop strategic planning through data-driven analysis with experts from the data-based PILs (e.g., 'the Innovation Team (i-team) at the City of Syracuse's Office of Accountability, Performance, and Innovation' and 'Minneapolis Innovation Team at the Office of Performance & Innovation'). In this regard, data-based PILs contribute to enhancing organizational operational capacity by providing support for efficient and effective performance management, producing better policy services and products for citizens, and achieving policy goals.

Systemic operational capacity

Systemic operational capacity includes coordination efforts by government and non-governmental organizations to perform policy actions to resolve public problems (Wu et al., 2015). Operational capacity at the system level is determined by the engagement level of policy networks and network coordination in the policy process (Wu et al., 2018). Clarity of roles and responsibilities of different agencies or organizations in the policy process is required for a high level of operational capacity. Capacity enabling collaboration occurs with other organizations, research institutes, and various policy domains for interdisciplinary knowledge and achieving the desired polity outcomes (Bettini & Head, 2018). Broader and stronger policy networks result from diverse experts and communities enhancing systemic operational capacity for policy implementation, which then can produce successful policy outcomes (Bettini & Head, 2018).

Collaborative coordination is increasingly required to address complex public problems (Wu et al., 2018). Data-based PILs seek to collaborate and partner with diverse policy actors, including government agencies, organizations, businesses, research groups, and startups to increase operational capacity for achieving better policy choices and implementation (Brock, 2021; Dekker et al., 2020; Lee & Ma, 2020; Salamon, 2002). For example, the German government has ordered state and local authorities to digitalize all public services by the end of 2022 (Fleischer & Carstens, 2021). In digitalization, bureaucratic actors at different levels of government work with external tech experts, IT providers, and service end-users to identify a target for digitalization. They then develop ideas and digital prototypes for user-friendly digital public services with their roles and responsibilities. Internal and external actors are brought in to collaborate and produce user-friendly digital public services. In addition, the external actors, including tech experts and product and process design consultants, respond to accountability issues (Fleischer & Carstens, 2021; Hjelmar, 2021; McGann et al., 2021). Such efforts can enhance policy implementation.

Furthermore, data-based PILs provide open spaces or platforms for collaboration and discussion across policy networks with diverse stakeholders and communities. They function with government officials, technologists, and citizens, to create solutions that meet citizens' needs (De Moor et al., 2010). The provision of an open space for discussion and collaboration that drives broader efforts to build a digital society is a key outcome of data-based PILs. Data-based PILs take initiative and perform experiments for building innovative solutions by leveraging multiple types of data and technology with collaborators. MediaLab Prado in Spain is a citizen laboratory and a meeting venue for the production of open cultural projects. Working groups collaboratively research and produce projects and programs in diverse topics, including art, science, youth and family, and mobility cultures. Through providing civic hackathons and other events, data-based PILs bring software designers and developers together to solve their communities' needs and demonstrate what is possible using technologies (e.g., CityLab Melbourne and Louisville Office of Civic Innovation).

By connecting and coordinating the roles of citizens, policy makers, and technologists through providing venues for collaboration, data-based PILs also promote the coherence of policy networks and communities. Such efforts are necessary for reducing technology barriers for policy makers and citizens, providing a better understanding of technologies, and supporting the coherence of policy networks to achieve successful and efficient policy implementation, including tech policy. For example, Tech Policy Lab seeks to minimize the gaps between policy makers and technologists for coherent understanding of policy implementation and helps to produce a more inclusive tech policy. In this regard, our analysis indicates that data-based PILs contribute to improving systemic operational capacity by building collaborative networks from diverse experts and stakeholders in policy processes.

Individual political capacity

The skills and competencies in political knowledge and experiences of understanding politics in policy processes are an essential capacity for successful policy actors (Wu et al., 2015). The individual political capacity with which a policy actor identifies other key policy actors and their interests, and the relationships among them (including political trade-offs), is an essential capacity for performing policy actions. Individual political capacity also includes skills of consensus building and negotiation to push policy actions forward (Wu et al., 2018). LABHacker in Brazil promotes e-democracy by developing actions and tools that increase social participation in the legislative process but do not directly support the enhancement of individual political capacity. This study found data-based PILs have not dealt substantially with individual political capacity, in comparison to their engagement with analytical and operational capacity.

Organizational political capacity

Developing organizational political capacity is necessary for successful governance (Dunlop, 2018). Governments and relevant organizations bring the public's attention to focus on a public issue and to actively take part in resolving a public issue (Post et al., 2008). Organizational political capacity is determined by the political legitimacy of an organization, the level of access to key policy makers, and engagement with stakeholders and citizens (Wu et al., 2018). Organizational political capacity can be enhanced by allowing citizens to monitor governments' activities, to participate in policy processes with key policy actors, and to influence outcomes in political aspects (Wu et al., 2015, 2018).

Data-based PILs focus on public and civic innovation, providing citizen innovation laboratories in which public officials and civil society participate in, collaborate on, and design experimental projects (Lewis et al., 2020). In venues provided by data-based labs, citizens discuss local challenges, design prototype ideas, do citizen-centered design, and provide innovative solutions to policy challenges. For example, MediaLab Prado in Spain serves as a citizen laboratory for producing open collaborative projects in diverse public issues and topics. NQNLab in Argentina also focuses on citizen participation to promote public innovation. From a transdisciplinary perspective, citizens at NQNLab debate and prototype ideas to resolve local problems. This process, supported by data-based labs, enables citizens to observe governments' activities and participate in policy processes with key stakeholders by enhancing the understanding and support for government programs and policies.

In addition, the political legitimacy of an agency or an organization, and accessibility to key policy makers, including ministers, are critical determinants of organizational political capacity (Salomonsen & Knudsen, 2011; Wu et al., 2018). Particularly, public organizations have certain political resources (Peters, 2015). The connections with their clients can bring powers on political decision-makers. In this regard, data-based PILs that are directly under a mayor's office or a minister's office have organizational political capacity. Overall, data-based PILs contribute to enhancing organizational political capacity by supporting the engagement of citizens and stakeholders in the policy process and its link to key policy makers.

Systemic political capacity

Systemic political capacity is critical because performs the groundwork for shaping the other eight types of policy capacity (Woo et al., 2015; Wu et al., 2015). Political capacity at the systemic level is distinguished and determined by the skills, competencies, and capabilities with which key policy actors participate in the policy process to sustain public support for pursuing policy goals and policy reform, producing desirable policy outcomes while resolving conflicts with other policy goals and policy actions (Wu et al., 2018). In this regard, compared with the other eight types of policy capacity, political capacity at the system level relates to accountability and legitimacy in the policy process, the level of trust in government, the framing of policy problems, policy-oriented beliefs and the level of public participation in the policy process to sustain the direction of policy at the systemic level of society. Based on these broad issues, a small number of data-based PILs are actively engaged with government and local communities in using open data and technology to build civically engaged technology ecosystems and ensure transparent and inclusive government. Thus, they play a role in building the infrastructure of policy subsystems. These activities create opportunities to inform the public about policy processes and help interested actors become participatory policy actors rather than simply voting (Rojas et al., 2014). In this regard, data-based PILs contribute to increasing the level of trust by pursuing transparent and accountable governance in alignment with the open data governance aforementioned in systemic analytical capacity. However, the engagement of data-based PILs in a systemic political capacity is limited and lacks practical and political impacts on the policy process.

From our review of data-based PIL policy capacity activities, Table 8 offers a summary overview across all 133 cases. This subjective assessment suggests that of the nine capacity types, data-based PILs strengths lay in analytical organizational and operational systematic policy capacities. Policy capacity was at least present in terms of developing all of the analytical and operational skills and competencies but nearly all of the labs have limited political capacity.

TABLE 8 Contribution levels of data-based PILs to policy capacity

	Skills and competencies		
Levels of resources and capabilities	**Analytical**	**Operational**	**Political**
Individual	++	+	–
Organizational	+++	++	+
Systemic	+	+++	–

Note: +++, strong; ++, acceptable; +, present; –, emerging.

CONCLUSION—IMPROVING POLITICAL POLICY CAPACITY

The purpose of this study was to explore how data-based PILs operate by reviewing 133 data-based PILs across the world. In addition, our review applied the policy capacity framework by Wu et al. (2018) to explore how data-based PILs contribute to enhancing nine types of policy capacity. Our analysis describes how data-based PILs enhance analytical and operational policy capacity at the individual, organizational, and systemic levels with limited political capacity.

Regarding political capacity at the individual level, data-based PILs can invest more in individuals' ability to consider political aspects of policy processes and better understand the attributes of political support for policy implementation. Some data-based PILs encourage individuals' participation in the policy process, but they have not directly involved individuals' political capacity and policy acumen or insights to analyze the interactions of different policy actors, each stage of the policy process, and surrounding politics of the policy process. Policy acumen, including understanding strategies, resources, actors, and their interests in the policy process, is a fundamental aspect of policy actors in analyzing the desirability and feasibility of policies (Wu et al., 2018).

Policy change and organizational change are difficult, particularly for public organizations, including the design of new working processes or forms, but have yielded public innovation (Peters, 2015). Public organizations or agencies are supposed to maintain a neutral position for political leadership, but they are not completely neutral policies and programs. Public policies and programs are the final output of government operation, and each policy or program is unavoidably related to political aspects (Peters, 2015). Organizations and agencies have their policy ideas and goals, which require political capacity to be implemented. The building of political capacity enables individuals, organizations, and systems to realize their policy ideas and goals for policy implementation and to produce desirable policy outcomes. In addition, in terms of political capacity at the organizational and systemic levels, it is necessary to not only produce collaborative networks between public, private, academia, nonprofit, and scientists but also promote networks to learn each operation of policy processes considering political values (Cairney et al., 2016). While we see the potential of data-based PILs to contribute to the infrastructure of policy subsystems by providing opportunities for policy actors to learn and interact, it is less clear that data-based PILs are providing that capacity, which can be valuable for policy learning.

In alignment with Belyaeva (2018)'s points that policy capacity should be considered a combination process of different capabilities, our analysis suggests that policy capacity is not a given set of skills, competencies, resources, and capabilities that already exists. Rather, it is an evolving set of characteristics or capabilities that can be expanded or even shrink over time. Our review of 133 data-based PILs suggests that policy capacity, particularly political capacity, should be further enhanced to produce desirable and sustainable policy outcomes. Recognizing the potential contribution of data-based PILs to policy capacity, future studies should focus on how data-based PILs and policy capacity can support policy learning and innovation in policy processes. Furthermore, future research should conduct case studies with in-depth analyses to explain more explicitly how capacity building and policy learning occur in data-based PILs.

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