QCA as an approach to make sense of micro-level data-centric practices for policy innovation: a *walk-through*

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Abstract

The paper explores the potentialities and challenges of using a comparative research method — Qualitative Comparative Analysis (QCA) — as a methodological approach for researching policy innovation. The paper argues for QCA to constitute a rigorous and systematic way to explore policy innovation using micro-level experimental and innovative practices in the public sector as the empirical base. Conceptually, we propose considering the importance of policy workers in policy innovation processes. This proposal addresses a gap in policy innovation research that appears to have mostly focused on entrepreneurship while under-appreciating other individual agency explanations of change (e.g., policy workers). Policy innovation researchers should therefore reframe the concept of policy innovation from an *out-based view* to a *process-based* view, while avoiding the development of ideographic knowledge. To address this issue, we provide a walk-through of using QCA as a methodological approach to investigate data-centric practices in the public sector. In the walk-through, we simulate the execution of the first three steps of approaching different cases of data-centric practices through QCA, identifying variables and calibrating them. Other researchers might find this approach useful to investigate similar innovative practices in the public sector in the perspective of policy innovation.

Keywords
policy innovation, micro-level policymaking, QCA, policy workers, policy learning, data-centric practices in the public sector, data-driven innovation

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1. Introduction: experimental practices for public sector innovation

"Innovation" is seldom presented as an unequivocally positive, even necessary, driver for improving a given context, sector, or state of things. The strong normative undertone that underlies this word might make us forget that *the concept* it describes does not represent a given reality but merely signals a rhetoric of change (Pollitt, 2011). Innovation propositions describe potential futures through narratives of what constitutes a "better" state of things in line with the proponent's vision. These *socio-technical imaginaries* (Jasanoff & Kim, 2009) are thus value-laden, instrumental and futuristic visions that contribute to and explain socio-technical change (Sovacool & Hess, 2017, p. 719). This implies that although "innovation" is, by definition, something yet to be realized, the low-hanging fruits it proposes through its narratives drive the work of many in the present.
This also applies to the public sector, which had been wrongly subject to the myth of being an unfruitful area for innovation (Cepilovs et al., 2013). Public sector innovation has been promoted in the last years thanks to movements advocating for efficiency and cost-savings in public organizations, such as the New Public Management and Evidence-Based Policymaking movements.

As the imperative of public sector innovation translated into the will of improving public organizations' routinary activities in terms of performance, quality and public acceptability, innovative and experimental methodologies and approaches have diffused in recent years, mostly through project-based activities led by adhocracies (Lindquist & Buttazzoni, 2021). Such diffusion led to the introduction of many-fold practices in the public sector connected with different innovation propositions and paradigms. Some examples are the use of non-traditional data, foresight and futures thinking, design methods, service innovation approaches and methodologies (e.g., service design), community-based and art-based initiatives (Hermus et al., 2020; Kimbell, 2022; Leoni et al., 2023; Tõnurist et al., 2017).

2. Framing micro-level innovation in institutional change: the dominance of entrepreurship

Pollitt & Bouckaert (2011) individuated four main types of processes for institutional change (Table 1):

- *Type A*: In line with the classical view of incrementalism, institutions would implement gradual adjustments (e.g., changes in budget allocation) that would never result in a radical change;
- *Type B*: When incremental adjustments of institutions are directed toward a clear direction, they will add up and eventually lead to a substantially different state of things (e.g., a gradual delegation of functions from national to regional bodies);
- *Type C*: Sometimes institutions would first advocate for change and appear open to a new direction, and then suddenly return to "business-as-usual"

- *Type D*: The conjuncture of several exogenous/endogenous variables (e.g., a crisis) would lead to an abrupt change of direction, followed by a new radical way of doing things.

Table 1. *Patterns of institutional change from Streeck and Thelen (2005) in Pollitt & Bouckaert (2011)*

		Result of change	
		Within path/incremental	Radical/transformation
Process of change	Gradual	A. Classic incrementalism	B. Gradual, but eventually fundamental change
	Abrupt	C. 'Radical conservatism' – rapid return to previous ways	D. Sudden, radical change (punctuation)

Most of the literature seems to have focused on type D (Pollitt & Bouckaert, 2011), considering change as abrupt punctuated events that radically transform otherwise stable directions that public institutions would follow. This view can be found in several theoretical perspectives, e.g., the *Punctuated Equilibrium Theory* (True et al., 2019) and *Multiple Streams Framework* (Kingdon, 1984). In these theoretical views, we can find the recognition of *policy entrepreneurs* as a special category of actors in processes of change.

Policy entrepreneurship (PE) has been chosen as the individual-agency explanation to understand how punctuated change is realized. The category of policy entrepreneur is used to identify certain actors in the policy process who are "*displaying social acuity, defining problems, building teams, and leading by example*" (Mintrom & Norman, 2009, p. 651). King and Roberts (1987) divide "*policy entrepreneurs*" from "*policy champions*", both being agents of policy innovation from outside (the former) and inside (the latter) governmental institutions. PE, it is assumed, can influence policy change and innovation, either from inside or outside the governments, given that certain propitious conditions arise (Béland & Haelg, 2020; Mintrom, 1997; Mintrom & Norman, 2009). Entrepreneurialism as a theoretical explanation can be traced to Joseph Schumpeter, for whom it was a central driver of creative destruction (Borrás & Edler, 2014, p. 8), and it has supported a large part of theoretical explanations of policy change dynamics (Mintrom & Norman, 2009). The concept of PE could be coupled with other theories that contemplate individual agency as a source of change. For example, Mintrom and Vergari (1996) proposed that PE can be integrated with the advocacy coalition framework (ACF) since policy entrepreneurs have a role in building and maintaining advocacy coalitions — which themselves influence governments toward policy change — building an analysis that integrates both theories in explaining policy change from the individual to the institutional level (cf. Mintrom & Vergari, 1996). The PE concept is still contemporary and employed in various study areas. For instance, within organizational studies, a theory of institutional entrepreneurship was proposed to expand institutional theory, which traditionally emphasized structure over agency (Battilana et al., 2009). *Institutional entrepreneurs* are conceptualized as change agents (i.e., individuals, organizations or groups of organizations) that drive and actively participate in changing in an institution (e.g., changing the organizing template of an institution). Battilana et al. (2009) provide an easy-to-grasp description of institutional entrepreneurs, contextualizing them in the UK's National Health Service:

> "The institutional logic of medical professionalism is the dominant institutionalized template for organizing within the UK's National Health Service (NHS). According to this logic, physicians are the key decision makers […] In this context, a clinical manager who initiates a change project aimed at implementing nurse-led pre-admission clinics or nurse-led discharge in a given hospital, thereby transferring both clinical tasks and some decision-making authority from physicians to nurses, qualifies as an institutional entrepreneur […]" (Battilana et al., 2009, p. 69)

Other examples are to be found in public sector innovation studies, for instance, where the PE concept can be used to consider how different agents operate to achieve change. It is the case with Bankins et al. (2017) that unified into the same theoretical perspective the typologies of *innovation promoters* (i.e., actors that promote innovative ideas by advocating for them at the political level) and *innovation champions* (i.e., actors that operate as "technical experts", working to overcome barriers to innovation, e.g., of technical or administrative nature).

3. Methodological issues with policy innovation at micro-level

While being extremely compelling as an explanatory category of abrupt policy changes, the concept of policy entrepreneurship might show several limits, especially when applied to *policy innovation*. In literature, *policy innovation* has been traditionally defined as adopting a policy in a context where it did not exist before (Berry & Berry, 1990) and studied *ex-post* through by considering policy learning dynamics as "lesson drawing", "policy transfer" and "policy diffusion" (Karch, 2021; Moyson & Scholten, 2018; Rose, 1991). This perspective might be deemed *output-based* as it essentially equates innovation with "reforms" (Windrum, 2008), focusing on new legislation and official decisions (documents) as manifestations of innovation. This output-based vision of innovation has been privileged to the detriment of a process-based vision of innovation (Vaz & Predeville, 2019) and been parallel to a general under-appreciation of micro-level innovation dynamics, especially those not falling into entrepreneurship (Karch, 2021). In particular, the role of *policy workers* (Kohoutek et al., 2018) in policy innovation dynamics has been undervalued. This might be rather problematic for appreciating the relationship between policy innovation and technological solutions in the public sector, as a social process of appropriation or domestication of technologies in different contexts is a central tenet of technological innovation and diffusion (Stewart & Williams, 2005).
Conceptually, considering the role of policy workers might help address these gaps. However, the process-based vision of policy innovation fundamentally requires refusing the idea that policy is an output detached from policy workers' activities. This shift requires

reconsidering the "policy process" ideal as "*policy-as-process*" (H. K. Colebatch & Hoppe, 2018). At the same time, a relevant methodological challenge exists in making sense of scattered practices without developing idiographic knowledge, as well-synthetized by political scientist Paul Sabatier:

> "Given the staggering complexity of the policy process, the analyst must find some way of simplifying the situation in order to have any chance of understanding it. One simply cannot look for, and see, everything." (Sabatier, 2007, p. 4)

Researchers interested in policy innovation "[…] *need to do better than to offer a rambling list of practices which may 'involve' policy*" (Colebatch & Hoppe, 2018, p. 7). In the following sections, we will provide a potential way to address cases of the problematic area briefly described above by using QCA to analyse cases of data-centric practices in the public sector.

4. A brief overview of QCA

Quantitative Comparative Analysis (QCA) was proposed by sociologist Charles Ragin in 1987 as a method to address the tension between variable-oriented and case-oriented approaches. By proposing QCA, Ragin intended to transcend the traditional qualitative/quantitative divide of social science (Ragin, [1987] 2014). The goal of QCA, therefore, is: "[…] to allow systematic cross-case comparisons, while at the same time giving justice to within-case complexity, particularly in small- and intermediate-N research designs." (Rihoux & Ragin, 2009, p. xviii). QCA is usually intended either as "an approach" to case construction or as "an umbrella term" for the three data analysis techniques (Berg-Schlosser et al., 2012; Rubinson et al., 2019). Rihoux and Ragin inscribe QCA into configurational comparative methods — i.e., a method that approaches case studies as a "complex configuration of properties" (Rihoux & Ragin, 2009, p. 6). Instead, Schneider and Wagemann (2009) consider QCA as a set-theoretic method that interprets social reality in terms of membership to a set of data:

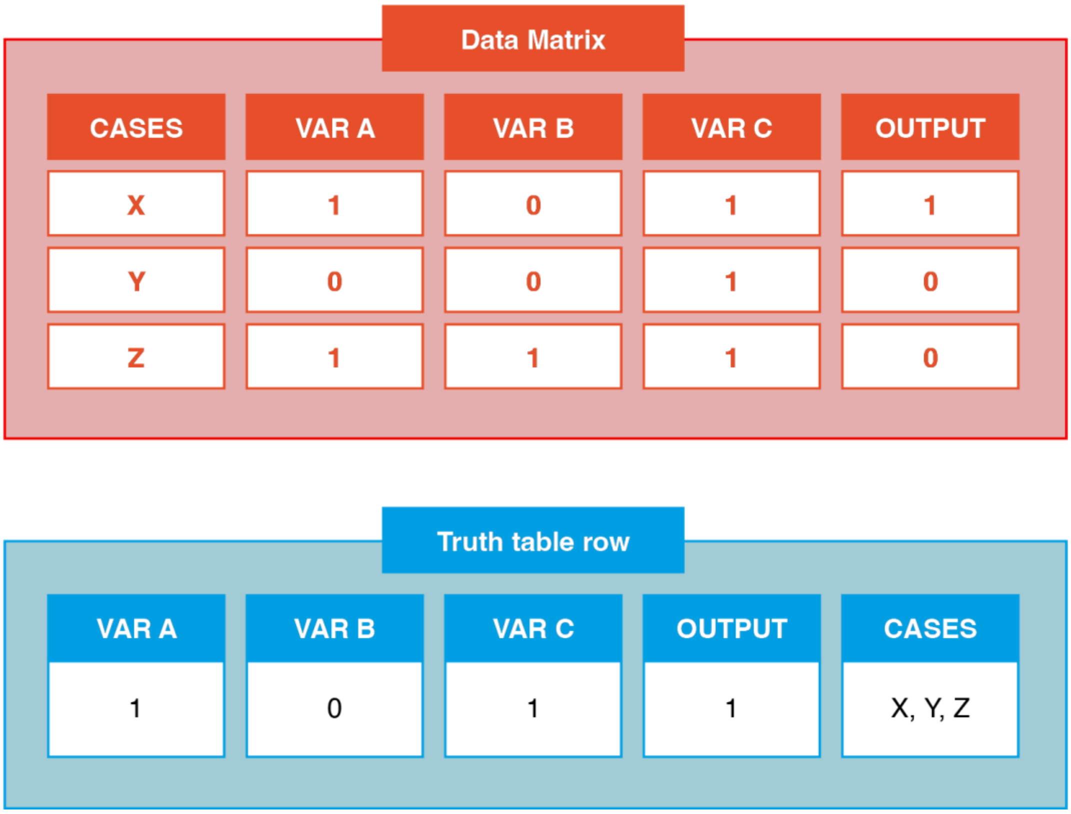
> "[…] the data on which set-theoretic methods operate are membership scores of cases in sets which represent social science concepts. For instance, France is an element of the set of European Countries whereas the USA is not. France's set membership score in this set is therefore 1, while that of the USA is 0." (Schneider & Wagemann, 2009, p. 3)

In essence, QCA as an approach implies that researchers see cases as the configuration of multiple variables (i.e., configurational perspective). The researcher identifies cases by inscribing them under these variables — or sets — with various membership degrees (i.e., adopting a set-theoretic perspective). These variables are defined as conditions and outcome variables. A researcher who seeks to employ QCA is encouraged to derive variables from theory, which has a decisive role in the process (Berg-Schlosser et al., 2012), and from substantive knowledge on the topic supported by empirical research (Gerrits & Verweij, 2016). These variables are then calibrated through three techniques:

crisp-set QCA (csQCA), multi-value QCA (mvQCA) and fuzzy-set QCA (fsQCA). “Calibration” refers to different choices of values that define the membership thresholds of a variable. While csQCA allows a variable to be set either as present (1) or absent (0), mvQCA and fsQCA consider a more nuanced set of anchor points: values that define the membership thresholds. Once the calibration thresholds are defined, the researcher interprets each case as a configuration of these variables, creating a *data matrix* that compares all variables for all cases.

At this point, the researcher utilizes QCA software to produce the so-called *truth table*, which shows all the possible figurations in the data matrix in relation to an *output variable*, finally proceeding with logical minimization (see Fig. 1). QCA is usually regarded as the optimal method to tackle causal mechanisms in terms of sufficiency and necessity (Thomann & Maggetti, 2020). For this purpose, in the later phases of the QCA procedure, statistical analysis is applied to the data matrix to derive the truth table. From the truth table, the necessary and sufficient conditions that generated the output are shown and linked with cases and expressed as parsimonious explanations in logical algebra (a process called logical minimization) (Rubinson et al., 2019).

Fig 1. Mock-up Visualization of a Data Matrix (red, above) and a Truth table row (blue, below)



5. A walk-through for approaching the policy innovation of data-centric practices with QCA

In this section, we will offer a walk-through for other researchers on how to use QCA as an approach to investigate micro-level cases in line with the perspective of policy innovation described in Section 3. As the contribution of this paper remains on the methodological aspects of policy innovation research, we will not offer empirical validation of the approach proposed but discuss it across three main steps referring to a potential example of application.

5.1. Step 1: Contextualizing and adapting QCA to the research's need

Data-centric practices in the public sector are experimental initiatives that aim to create value from non-traditional data in the public sector (Leoni et al., 2023). These practices occur as policy actors translate digital innovation agendas' goals connected to data-driven innovation into concrete projects and experimentations (Lanza, 2021), often signalling an attempt to turn non-traditional digital data into a new source of evidence for policy. Therefore, these data-centric practices concretely manifest a worldwide political commitment to the ideal of the data-driven public sector (Ubaldi et al., 2019). Data-centric practices should be considered relevant by policy innovation scholars as they might influence new norms, directives, and legislations on data and digital innovation in government, bridging innovation ideals with ground-level activities.

In general, for QCA, innovative practices might represent an obstacle, as the optimal use of this method would depend on a theoretical understanding of the phenomenon to which it applies (Thomann & Maggetti, 2020). Since data-driven innovation in the public sector appears as a theoretically under-developed phenomenon (Leoni et al., 2023), QCA cannot be used to prove or disprove causation or validate descriptive typologies, but only as a methodological approach to explore empirical cases — i.e., to synthesize, summarize and reflect on the data rigorously, running a qualitative assessment on cases' comparison. While QCA as an approach is perfectly legitimized by literature (Berg-Schlosser et al., 2012, p. 15), the lack of theory hampers QCA's potential. Therefore, the first step in using QCA as a methodological approach implies rethinking its application — from using it as a method *sensu stricto* (or as a data analysis technique for deriving parsimonious explanations) to leveraging it for rigorous data collection procedure and driving an iterative back-and-forth from assumptions to cases (Pagliarin et al., 2022; Rihoux & Lobe, 2009; Thomann & Maggetti, 2020).

5.2. Step 2: Identifying macro-level and micro/meso-level variables

In QCA, the researcher should describe the cases through a series of conditions variables and one output variable. For its application to data-centric practices in the public sector, we propose considering the cases as the conjunction of variables at the macro and meso/micro-level. The macro-level conditions should be seen as structural elements that describe the context in which cases happen, and they concern the enabling condition of using data in the different public sector contexts. The meso/micro-level conditions, on the other hand, pertain to the level of social groups involved in data-centric practices. In line with the conceptualization proposed in section 3, policy learning is finally considered the output variable — i.e.; it is assumed that data-centric practices represent a processual innovation that can be investigated by considering updates in individual cognitive/normative beliefs (Leoni, 2020). Because of the lack of theory discussed earlier, it is important to stress that the conditions variables are not considered theoretically linked to the output variable. The choice of policy learning as an output variable is based on a substantiated framing of policy innovation (Leoni, 2020), that considers the individuality of policy workers as a relevant dimension to probe policy innovation dynamics since these actors mediate between policy goals and the context of practice (Turnbull, 2013). This choice can be different for researchers investigating other phenomena connected to policy innovation.The macro conditions proposed for data-centric practices, which need to be isolated for applying QCA, are derived from two existing national-level indicators developed by the OECD; the *OURdata Index* (ODI) (OECD, 2020b) and the Digital Government Index (DGI) (OECD, 2020a). The ODI was first piloted in 2015, then published officially in 2017 and 2019 as a national indicator of progress in digital innovation, focusing on government data re-use assessed on three main dimensions (Lafortune & Ubaldi, 2018, p. 5). The DGI, on the other hand, was piloted more recently (2019) to evaluate how governments were progressing toward digital government (Ubaldi & Okubo, 2020).

The DGI is based on a composite score of six dimensions considered to characterize the ideal digital government. Data used in ODI and DGI are collected through surveys administrated to high-level public officials in OECD countries governments and other qualitative sources (Lafortune & Ubaldi, 2018; Ubaldi & Okubo, 2020). These indicators are both proposed as the first to focus on how governments make data and digital government central elements for public value creation and innovation (Lafortune & Ubaldi, 2018). The three macro-level structural conditions included in QCA were respectively based on the second and third dimensions of ODI, while the third was based on the data-driven government dimension of DGI. In order, these were:

- *Data Accessibility*
  The extent of provision of government data and associated metadata in open and re-usable formats within a national government.

- *Data Culture*
  The extent to which a national context promotes the re-use of government data inside and outside the public sector.

- *Data Governance*
  The degree of presence of legal frameworks, specific regulations and responsible roles/organizations for government data sharing and re-use.

Moving to the meso/micro-level conditions, in our example, these can be identified at the level of the social groups. Thus the factors usually associated with social policy learning can be considered by looking at several individuals and intra-individual characteristics of the social group involved in data-centric practices (Riche et al., 2021). Starting from these characteristics, and based on practical considerations about which conditions would be feasible to measure, the following meso/micro conditions are proposed for data-centric practices advanced:

- *Political Support*
  Duration and quantity of social interactions are correlated to policy learning (Resh et al., 2014; Riche et al., 2021). In data-centric practices, it is imaginable that the prolonged interaction of policy workers over non-traditional data depends on the political support for data-centric policymaking in the form of endorsement, dedicated budget or personnel time.

- *Leadership*
  The presence of leaders or respected mediators, who can overview the process and mediate across actors, is suggested as an essential element for a policy learning network which features several types of actors (McFadgen & Huitema, 2017; Resh et al., 2014; Riche et al., 2021).

- *Experience*
  Policy learning depends on the previous competencies and types of knowledge which policy actors bring into a learning network. The presence of knowledgeable figures from which the other actors can learn, is supposed to influence learning.

- *Diversity*
  The diversity of the profiles and backgrounds of the learning group is seen as an influential factor for learning. The similarity of these views (homophily) can facilitate learning (Riche et al., 2021) but can also hinder it (Resh et al., 2014).

Conditions POL, LEAD, EXP and DIV should also be based on preliminary insights and data collected as the researcher interacts with the cases, e.g., from interviews with one or more key informants.

5.3. Step 3: Calibrating variables

After all conditions and outcome variables are defined, the QCA procedure requires a step called calibration. As a set-theoretic method, QCA describes cases according to set membership. Each of the variables identified (conditions and outcome) constitutes a set, i.e., a concept that either describes the case or not (Schneider & Wagemann, 2009, p. 24). The researcher thereby proposes the set membership for each variable through the calibration procedure, through which the researcher aims to establish thresholds that define the possible degree membership. Depending on the QCA technique employed, the number of thresholds can range from "0" (indicating non-membership) to "1" (indicating full membership). Several practical indications and techniques exist in the literature on performing calibration according to the best standards. Generally, it is suggested that calibration should be determined by the researcher's substantive knowledge of the case, preliminary data collection and theoretical assumption on the relation between conditions and outcome; therefore, calibration highly depends on each research (Berg-Schlosser & Meur, 2012). The researcher is encouraged to reflect thoroughly on the meaning of each variable and what it means for a case to be fully a member of that set or not (Rubinson et al., 2019). Whenever possible, calibration should be based on data that are external to the pool of cases considered (Schneider & Wagemann, 2009). In our example, this suggestion applies to macro-level structural enabling conditions of cases. Calibration could also be based on qualitative data collected within the cases, for example, interviews with key Informants. In this example, we propose to work with a direct calibration through a fuzzy-set 4-point threshold (0; 0.33; 0.67; 1) for most of the variables, as this scale seemed adaptable both to quantitative and qualitative data and widely adopted (Basurto & Speer, 2012). For the calibration of the macro-level structural variables (GOV, ACC, CULT), each case's national context score could use the indexes as a reference. The score for each case national context in the index can be normalized on a "0-1" scale (with 0 being the lowest country in the ranking and 1 the highest). The score for each variable in each case country can also be normalized in the same way and approximated to the closest threshold. This whole process, however, should not be done mechanically but critically, considering both the indexes and the insights from key agents interviewed.

The micro/meso variables should be calibrated from qualitative insights and data collected from cases. For example, the calibration of Political Support (POL) might be based on the reported presence or absence of explicit support for the data-centric practices by explicitly asking the policy workers involved if the initiative received a dedicated budget, assigned staff or explicit endorsement. This type of variable would be either present or absent. Similarly, the calibration of leadership (LEAD) might depend on the presence of actors or organizations clearly regarded as leading figures within the cases. As these figures would be either present or not, the calibration would be strictly "0" or "1". The calibration of Experience (EXP) can be based on years of working experience in government reported through a survey or interviews. The percentage of respondents declaring "from 5 to 10 years" and "more than ten years" of working experience on the total sample can be used to assign the threshold. The calibration of Diversity (DIV) may be based on the number of affiliations reported by respondents in the survey. Since this variable might be quite relative, the case with the highest number of discernible affiliations will set the maximum threshold for the variable (value of 1), and the other cases will be defined accordingly. Finally, the calibration of learning (LEAR) can be based on the number of possible self-assessment statements expressed by each group on cognitive or normative learning on policy-related topics, e.g., the policy problem, policy tools, public services and actors. For example, in a case with ten individuals, the total of potential statements that could be expressed for these questions would be 80. The highest number of preferences for each grade of the Likert scale can be used to assign the score for the learning variable in that case. Table 2 sums up the calibration procedure described in this section, with description for each fuzzy-set.

Table 2. *Variables for data-centric practices and their calibration*

Code	**Name**	**Set description.** *Full membership (1) in this set indicates…*	**Data Source for assigning membership**	**Fuzzy-set value definition**
Macro level variables – structural enabling conditions				
GOV	Data Governance	National ecosystem with a mature data governance framework for value-creation from public sector data (e.g., data policy, data governance frameworks, responsible public bodies).	Ubaldi & Okubo, 2020	0 = data governance is lowly developed; 0.33 = data governance is below average; 0.67 = data governance is above average; 1 = data governance is very highly developed;
ACC	Data accessibility	National ecosystem where public data are widely accessible in open and re-usable formats.	Lafortune & Ubaldi, 2018	0 = data accessibility is very low; 0.33 = data accessibility is below average; 0.67 = data accessibility is above average; 1= data accessibility is very high;
CULT	Data Culture	National ecosystem with high data literacy and where the re-use of data inside and outside government is incentivized.	Lafortune & Ubaldi, 2018	0 = data culture is very low; 0.33 = data culture is below average; 0.67 = data culture is above average; 1= data culture is very high;"
Meso/Micro-level variables – group level conditions				
POL	Political Support	The case had dedicated budget and resources / is supported by institutions. The process has been carried out for long time.	Insights from key informants	0 = absence of political support (no dedicated budget, short time given to interacting) 1 = presence of political support (dedicate budget or staff, long time given to interacting)
LEAD	Leadership	Presence of leading figures with strong commitment and clear vision on data and policy problems. These leaders supervise the project and mediated across actors.	Insights from key informants	0 = absence of leadership 1 = presence of leadership
EXP	Experience	The case had an high percentage of actors with a long experience of working in government on the total of individuals involved.	Survey	0 = case with zero or few actors with past working experience in government 0.33 = more low than high presence of actors with past working experience in government; 0.67 = more high than low presence of actors with past working experience in government; 1 = high level of past working experience in government

DIV	Diversity	The case had a high number of organizations involved with respect to the sample	Survey	0 = case with the minimum number of organizations involved with respect to the sample. 0.33 = case with low number of organizations involved with respect to the sample; 0.67 = case with high number of organizations involved with respect to the sample; 1 = case with the maximum number of organizations involved with respect to the sample;
Dependent/outcome variable – self-reported individual policy learning				
LEAR	Learning	The majority of respondents "Strongly Agree" on having learned (gained new information, changed beliefs) by involvement in the case	Survey	0 = the majority of respondent "Strongly Disagree" on having learned (gained new information, changed beliefs) by involvement in the case 0.33 = the majority of respondent "Disagree" on having learned (gained new information, changed beliefs) by involvement in the case 0.67 = the majority of respondent "Agrees Disagree" on having learned (gained new information, changed beliefs) by involvement in the case 1 = rhe majority of respondents "Strongly Agree" on having learned (gained new information, changed beliefs) by involvement in the case

6. Reflections and outlook

The walk-through presented here intends to spark an interdisciplinary discussion on several aspects touched by the paper, which are of theoretical/methodological nature:

- The relevance of experimental practices in the public sector, due to the governments' attempts to fulfil their innovation goals, urges researchers to consider policy innovation from a *process-based* perspective. The abandonment of an out-based perspective of policy innovation also fundamentally implies recognizing innovation not only through ex-post assessments of *authoritative instrumental choices* (e.g., through official documents publication or historical data). Accordingly, researchers might need to reframe the "policy process" ideal into "policy-as-process" (H. K. Colebatch & Hoppe, 2018) — i.e., accounting for the practices that make policymaking and how they interplay with innovative elements (e.g., non-traditional data).

- Considering policymaking as a practice, without falling for ideographic knowledge, compels researchers to a multi-level view that connects the high-level abstract policy goals to the level of policy workers that re-problematize policy goals into their contextual settings (Turnbull, 2013). In this view, QCA should be seen as a tool to navigate cases' complexity (Gerrits & Verweij, 2016) or, in other words, to account for cases as multi-level conjunctural causation of variables that express phenomena of interest.

- The policy innovation research community ought to acknowledge interdisciplinarity. Working on research methodologies and methods might constitute a fruitful way to embrace interdisciplinarity. Research methods such as QCA not only provide rigorous procedures for collecting data and analyzing empirical data; but also offer ways to translate and mediate disciplinary silos by revealing how epistemic communities might *think differently* about the same phenomena. In this sense, entry-level methodological walk-through, tutorials and tools (e.g., digital and open source) will be needed to dispel the obscurity that often surround social science methods; allowing their creative appropriation and reuse across disciplines.

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