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Barriers to the Digital Transformation of Infrastructure Sectors

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Abstract

Digital technologies can be important to policy-makers and public servants, as these technologies can increase infrastructure performance and reduce environmental impacts. For example, utilizing data from sensors in sewer systems can improve their management, which may result in better surface water quality. The utilization of such *big data* from sensors is however not only a technical issue, but depends on individual, organizational and institutional factors as well. Our article identifies barriers to the evaluation of data from sewer systems, as one type of data utilization. We employ fuzzy-set Qualitative Comparative Analysis (fsQCA) to compare Swiss sub-states and find that three different barriers at different levels can each hinder data evaluation on their own. More specifically, either a lack of vision at the individual level, a lack of resources at the organizational level, or administrative fragmentation at the institutional level hinder the evaluation of data. Findings suggest that taking into account different levels is crucial for understanding digital transformation in public organizations.

Keywords: digital transformation, data utilization, infrastructure, wastewater, Switzerland, QCA.

1. Introduction

The on-going digital transformation has the potential to increase the performance of public infrastructures and – as one consequence – reduce environmental impacts. Digitalization is also gaining ground in the public sector (Giest 2017) and, more specifically, in the domain of public infrastructure (Apráez and Lavrijssen 2019). An increasing number of municipal and regional authorities have started experimenting with applications relying on information and communication technologies (Arduini et al. 2010; Guenduez et al. 2018) to increase performance and efficiency of their services and operations.

Digital transformation is spurred by technical advancements in sensor and data transmission technologies which have enabled more sophisticated instrumentation and highly accurate measurements, resulting in what is often termed big data (although the concept is vague, see Connelly et al. 2016). Big data is large in volume, features incoming real-time data streams and requires employment of advanced analytics or algorithms (Klievink et al. 2016; Höchtl et al. 2016). Despite concerns over data security, over-reliance on data and potential benefits for the resolution of complex problems (Millar 1972; Giest and Samuels 2020), big data is also acclaimed for providing an important potential for higher performance and more efficient services (Vydra and Klievink 2019). For instance, the public water utility Denver Water has started to use big data to proactively identify trends that could point out to potential system failures before they arise as problems (Heaton 2013). Big data is also used by the public transportation authority of Singapore to reduce crowding in congested areas (Maciejewski 2016). Studies have further analyzed the rollout of smart meters for small consumers in the energy sector (Apráez and Lavrijssen 2019).

Despite potential benefits, the utilization of big data is still limited, especially in the public sector (Klievink et al. 2016; Vydra and Klievink 2019). The literature focusing on social factors influencing digital transformation has mostly studied the mere adoption of new technologies, whereas factors favoring or hindering the effective utilization of data have been overlooked (Sun et al. 2016; Surbakti et al. 2019; Maciejewski 2016). Digitalization per se does often not provide immediate benefits, but rather produces large amounts of data potentially leading to data wasting (Mergel et al. 2016). Yet, as the volume of data produced by new technology is increasing exponentially, the need for data analytics, processing and interpretation of data is also growing (Millar 1972; Ingildsen and Olsson 2016; Giest 2017; Apráez and Lavrijssen 2019) in order to avoid a disconnect between the hopes put into data production and the reality of data utilization (Giest and Ng 2018).

In order to understand how public authorities utilize newly available data of infrastructure systems and what challenges impede its effective use (see Giest and Raaphorst 2018), we analyze urban water management divisions of Swiss sub-states (Rieckermann et al. 2017). Based on a combination of deductive (theoretical arguments from different strands of literature) and inductive (exploratory and semi-structured expert interviews) approaches, the study explores what (combination of) factors act as barriers to the evaluation of data. The Swiss sub-states are characterized based on in-depth interviews and document analysis, and compared through Qualitative Comparative Analysis (QCA).

By doing so, we make three contributions to the literature. First, we address a less researched but crucially important aspect of digital transformation, that is, the utilization of data, as compared to the mere adoption of new technologies (Sun et al. 2016; Maciejewski 2016; Mergel et al. 2016; Giest 2017; Surbakti et al. 2019). Second, we bring together perspectives from policy and innovation studies, information technology, and environmental engineering in an interdisciplinary exercise. This results in a comprehensive set of potential barriers to digital transformation on individual, organizational and institutional levels that has not been jointly assessed in the existing literature. Third, while many conceptual articles with illustrative examples (Lavertu 2016, Giest 2017) or single case studies (Barns et al. 2017; Giest and

Raaphorst 2018) deal with big data and politics, barriers to digital transformation have rarely been studied in a medium-N comparative setting with potentially important contextual variations across cases (Chatwin et al. 2019).

The remainder of this article is structured as follows. In the next section, we compile insights from the literature with a focus on digital transformation and barriers at different levels. After introducing our specific research context in section 3, we combine deductive logic with inductive reasoning using our case knowledge and findings from expert interviews. We identify potential barriers to the evaluation of data from sewer systems which we describe in section 4, along with the analytical method. We then present the results of our analysis followed by a discussion. The article ends with conclusions that discuss the broader applicability of results, limitations of the analysis and future research questions.

2. Politics, big data and barriers to digital transformation

2.1 Potential benefits and critical voices

Digitalization can affect the entire policy cycle (Höchtl et al. 2016), from the input side of policy processes, through innovations in democratic participation (Janssen and Helbig 2018), to its end, through the implementation of policies through public e-services or data-based evaluation of policies (Lavertu 2016). The digital transformation has often been said to pave the way for more evidence-based policymaking in public administrations (Höchtl et al. 2016, Giest 2017). According to some, concepts such as "open government" (Chatwin et al. 2019) or "digital-era governance" have replaced paradigms such as new public management (Dunleavy et al. 2005).

There is however a large diversity of critical voices. Already Millar (1972) criticizes a potential bias towards mechanistic and abstract solutions for human problems, and a failure to properly take into account limited human and organizational abilities. Lavertu (2016) discusses the problems of potential misperceptions of organizational performance due to publicly available data to actors outside of public agencies. Most recently, discussions have involved a potential bias against digitally illiterate or minority groups (Giest and Samuels 2020).

2.2 Barriers on different levels

The disconnect between data production and data utilization (Giest and Ng 2018) is not only reflected in these critical voices, but is further exacerbated by the fact the digital transformation also requires human and organizational capacities for data analytics, processing and interpretation of data (Millar 1972; Ingildsen and Olsson 2016; Giest 2017; Apráez and Lavrijssen 2019). While technical advancements in digital technologies promise a multiplicity of benefits, their implementation into existing organizational structures that would allow the actual reaping of benefits is often challenging (Shearmur and Poirier 2016, Wang and Feeney 2014). Long established structures and procedures of policymaking and implementation tend to be sticky, public administration actors generally rely on traditions and established "ways of doing things" (DiMaggio and Powell 1983), and the stable mind-set of any organization will support only a limited range of innovations (Walker 2006).

Previous findings in innovation studies, public administration, management and information technology show that similar to the adoption processes of technological innovations, the utilization of big data in organizations is also contingent upon several factors that can be attributed to three levels: individual, organizational and institutional factors (Klievink et al. 2016; Sun et al. 2016; Surbakti et al. 2019). Similarly, the technology-organization-environment (TOE) framework claims the adoption of an innovation to be dependent on technological, organizational and environmental contexts (i.e. institutional and geographical structures) that the organization in questions is part of (Tornatzky et al. 1990). Finally, also actor-centered institutionalism in political science or public administration studies (Scharpf

2018) emphasizes that actors’ (individuals or organizations) rational behavior is influenced by the institutional context and cultural norms. Factors on all three levels of individuals, organizations and institutions should thus be jointly analyzed for a full understanding of digital transformation in public organizations.

2.3 Individual-level factors

Individual characteristics such as attitude, belief and vision of managers can be highly important for organizational innovation (Rogers 2003), including the use of big data (Corbett and Webster 2015). Managers’ cognitive orientation and vision towards the perceived value of data-driven management is also referred to as “technology acceptance” (Venkatesh and Davis 2000). Klievink et al. (2016) refer to this attribute as internal attitude of individuals, defined as “capability to develop internal commitment and vision for new processes and systems, especially openness towards data-driven decision-making”. For example, a high employee engagement in terms of personal commitment and presence of championing figures who actively promote big data are important for its use in organizations (Surbakti et al. 2019). Taking into account the perceptions of public managers helps to assess why uses of big data remain very limited in the public sector (Mergel et al. 2018; Guendez et al. 2020).

2.4 Organizational factors

The literature emphasizes two organizational factors important for the innovativeness of an organization (Clausen et al. 2019). First, a lack of resource capacity to deal with data by relevant actors can represent a major bottleneck for digital transformation (Giest 2017). Human resources are found as one of the most important factors affecting organizations’ adoption of data utilization practices (Sun et al. 2016; Comuzzi and Patel 2016). More specifically, in case of big data, the adequacy of IT-literate personnel and availability of data science expertise are critical for organizations to develop a data use strategy (Klievink et al. 2016).

In addition to human resources, a data oriented innovation culture is essential for successful initiatives of big data utilization (Surbakti et al. 2019; Marshall et al. 2015). For instance, municipalities advanced in e-government initiatives are more likely to be the ones with higher in-house ICT (information and communications technology) activities and intranet infrastructure (Arduini et al. 2010). An established digitalization culture across the entire organization can indicate not only the readiness but also the experience required for incorporating data into internal planning and decision-making processes. Civil servants benefit from organizational support for their potential interest in digital transformation, through, for example, training or sharing of data among government departments (Giest 2017). As many organizations still struggle to transition from paper-based management (Austin 2018), the lack of an established digitalization culture is likely to impede the utilization of data.

2.5 Institutional factors

Organizations may face various types of institutional pressure originating from dominant norms, expectations and cognitive frames, acting through social embeddedness and networks of an organization (DiMaggio and Powell 1983; Williamson 2000). We refer to institutional factors as those factors that constrain the organization as embedded in its institutional arrangement. Such institutional arrangements can influence transaction costs (Williamson 2000; Andrews-Speed 2016), an important factor especially when dealing with data processing and interpretation. Increased diversity in size and number of partners with whom data is exchanged may correspond to an increased variety of data sources and formats, as well as different demands regarding organizational and coordinative efforts when it comes to receiving and treating data. This may lead to a larger burden on authorities as one end user of data since merging data from diverse sources can require significant effort and time (Austin 2018). This institutional barrier has also been described as being due to that existing administrative and institutional structures define the way data is collected, analyzed and used, leading to "data silos" (Giest 2017).

3. Utilizing data from sensors in Swiss sewer systems

Smart metering, in the context of urban water management, refers to the installation of sensors and data transmission technologies in sewer systems (Apráez and Lavrijssen 2019). Such sensors allow obtaining real-time information on the system's actual performance (leakages, outages, etc.) and its impact on surface water quality, thus creating benefits for operators, planners and authorities (Fletcher and Deletic 2007; Langeveld et al. 2013). For operators, the information gained from smart meters is key for real-time operational decision-making (e.g. in case of blockages or malfunctioning of pumps) and for a better understanding of the system's capacity and behavior. For planners, using available long-term data series for model validation and calibration, reduces uncertainties and thus prevents unnecessary investments, leading to an improved infrastructure planning process (Korving and Clemens 2002). Moreover, responsible authorities who receive periodical performance reports could potentially use this information for compliance assessment and more evidence-based decision-making regarding both the operational performance and the systems' efficacy for surface water protection (Rieckermann et al. 2017).

In Switzerland, where sewer systems are mainly managed publicly, an increasing number of municipalities install sensors without being obliged to do so (Rieckermann et al. 2017). However in practice, sensor data is currently not often shared with other beneficiaries such as authorities, or not analyzed for evaluating the system's performance (Manny et al. 2018). A scenario where government is aware of a data gap and data is potentially available in different formats corresponds to a secondary data gap (Giest and Samuels 2020), as compared to a primary data gap where data is unavailable.

This analysis compares 23 Swiss sub-states (see Table A.1 in Appendix A).[1] In Switzerland, the overarching goals of quality, security and resource protection are embedded in the Swiss Constitution and in the national legislation (such as the Water Protection Act). In federalist Switzerland, the regulative and executive competences on water and infrastructure management are mostly at the sub-state level, and operational competences for the discharge and treatment of wastewater have typically been delegated to municipalities (Luís-Manso 2005). Sub-states are thus important political entities in Swiss water and infrastructure politics, similar to Water Boards in the Netherlands, Water Authorities in France, or Environmental Ministries of German Länder.

4. Methods

4.1 Data collection

We relied on a two-step approach for data collection. First, we conducted nine exploratory expert interviews (with operators, authorities, engineers, and researchers) to identify specific conditions that may be particularly relevant for our analysis, based on the general three-folded structure of factors (i.e. at individual, organizational and institutional levels) derived from the existing literature. In our study context, we conceptualize these factors as barriers to digital transformation (see Figure 1). Second, we gathered data from semi-structured face-to-face interviews with 23 sub-state representatives (data stems from questionnaires for three sub-states) in October 2017. Sub-states' representatives who provided the relevant information are affiliated to the sub-states' division of urban water management. The interviews lasted between

[1] In the sub-states AI, BS and GE, the authority operates most parts of the sewer system. Any operational task, e.g. installation of sensors or data gathering, lies in the responsibility of the authority and not as usual in municipal hands. Consequently, we exclude these sub-states from the analysis.

one and three hours, and included questions on the infrastructure, sensors, using data as well as the representative's preferences for given policy instruments (see Table 1 for detailed interview questions used in our analysis).

4.2 Qualitative Comparative Analysis (QCA)

We apply Qualitative Comparative Analysis (QCA) as we apply a mix of deductive and inductive strategies to identify configurations of barriers at different levels. QCA is ideally suited for this task, because it identifies different combinations of conditions linked to an outcome (Ragin 1987; Schneider and Wagemann 2012; Rihoux and Ragin 2009). The method, which is based on set-theory and Boolean algebra, is designed for the comparison of usually a medium (5-50) number of cases. Thus, the number of Swiss sub-states (26, from which we include 23 in our analysis) aligns well with the medium-N focus of QCA (Schneider and Wagemann 2012). In similar settings, scholars have used QCA to compare Swiss sub-states (Sager and Rielle 2013), to assess the influence of water stress, geographic and economic factors on water recycling in Australia (Kunz et al. 2015), or the use of body-worn cameras by policy in US states (Pyo 2020).

Fuzzy-set QCA (fsQCA) relies on data points on an interval scale (from 0 to 1) to identify their degree of membership in the sets of the outcome and the conditions. A so-called truth table is the basis of the analysis and presents all observed and logically possible configurations of conditions (see Table 2). For each configuration of conditions (corresponding to a row in the truth table), the researcher then assesses the degree to which it is empirically related to the outcome. The assessment of this relation is based on fuzzy-set values of all cases and is indicated by a consistency score. Configurations that are consistently related to the outcome are included in the analysis. QCA then reduces the configuration of conditions that are related to the outcome by eliminating redundant conditions and finally identifies sufficient conditions related to an outcome. In this work, the analysis was performed using the R-packages “QCA” (Dusa 2019) and “SetMethods” (Oana et al. 2018).

4.3 Operationalization and calibration

In this section, we combine the factors identified from literature (deductive logic) with case knowledge and insights from expert interviews (inductive logic) to derive conditions particularly relevant for our analysis. We end up with four conditions that can be assigned to the three levels identified based on the theoretical discussion (see Figure 1). We then describe the calibration procedure – that is, the assignment of fuzzy-set values to different states of the outcome and conditions – and explain our choices on fuzzy-set anchors for the outcome and each of the four conditions. Tables A.2 and A.3 in Appendix A provide an overview on raw and calibrated data.

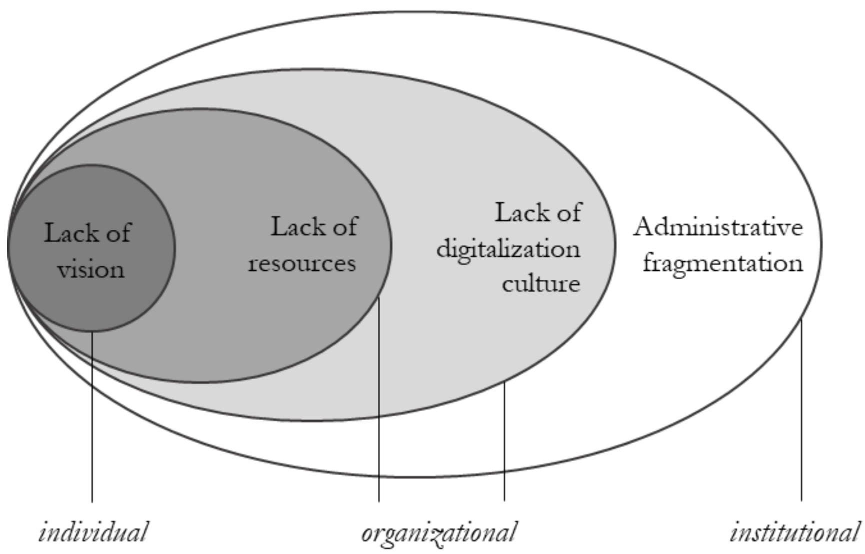

Fig 1. Identified conditions hindering the evaluation of data by Swiss sub-states: Lack of vision at the individual level, lack of resources and lack of digitalization culture at the organizational level and administrative fragmentation at the institutional level

Outcome: No data evaluation (NO-EVA)

Given that the analysis focuses on barriers, we describe the outcome by whether sub-state authorities do not evaluate data on the performance of sewer systems. The outcome NO-EVA is measured by an interval-scaled variable which is associated to the multiple-choice interview question: “How often is monitoring data evaluated by the sub-state authority?” Fuzzy-set calibration is then based on respective answers. A full set membership score (1.0) is assigned to cases where data is not evaluated. A full set non-membership score (0.0) is given to cases where sub-states’ representatives evaluate data after relevant surface water pollution incidents (e.g. heavy rainfalls) and additionally in a periodic scheme, either monthly or yearly. Generally, both frequencies, i.e. monthly or yearly, would be a comparatively satisfactory state of practice and would provide useful evidence on the system’s performance. We assume that evaluating data at least after relevant pollution incidents is already a step towards evidence-based management and thus assign a fuzzy-set score of 0.67, which is, for instance, the case in FR. The cross-over point of 0.5 is set for the shift from an incident-based towards a periodic data evaluation. If data evaluation solely occurs periodically without incident-based evaluation, we assign a fuzzy-set score of 0.33.

Condition 1: Lack of vision (LACKVIS)

In the theoretical literature, attitudes, beliefs and vision of responsible individuals are considered critical in creating the impetus for innovation in general (Rogers 2003), and data-driven management more specifically (Corbett and Webster 2015). The role of those individuals responsible for the respective administrative divisions was also emphasized as a crucial condition for the evaluation of data from our exploratory interviews. For example, our expert interviews revealed that evaluating data is often rather recognized as a hobby of those skilled to deal with data instead of generally acknowledging it as an important task that may reduce surface water pollution. Therefore, lack of vision on the part of individuals such as division or department heads in sub-state authorities is considered a potential barrier for the evaluation of data from sewer systems.

The condition *lack of vision* (LACKVIS) is calibrated based on an ordinal variable that reflects the openness of the sub-states' representative towards a future scenario of "data-driven management of (smart) sewer systems"[2]. Full membership (1.0) for the set LACKVIS is assigned if the interviewee disagrees to the outlined scenario, full set non-membership (0.0) is given to a full scenario acceptance. An additional set membership score of 0.4 is introduced to consider if interviewees agree only under specific preconditions, e.g. if competences and responsibilities are to be distributed more clearly. We assume that such a situation lies more within the set of agreement than disagreement which is why a score of 0.4 is assigned. Some sub-state representatives (e.g. SO, TG) welcome data-based management of sewer systems. On the contrary, other representatives (e.g. GR, OW) argue that sensors in the challenging sewer environment are not yet state of the art technology and are rather convinced that either the technology is not leading to any form of improvement or that the vision is impossible to ever materialize. Hence, such cases are assigned a score of 1.0.

Condition 2: Lack of resources (LACKRES)

As suggested by the literature, a lack of personnel resources and capacities at the organizational level (Klievink et al. 2016) stands out as another potentially impeding factor. In line with the literature, findings from exploratory expert interviews indicate that personnel capacities are

[2] This scenario was presented during the interview: "Combined sewer overflows and sewer system are equipped with multiple sensors. Data is continuously transferred live and wireless to a central control system, automatically checked and then archived. Authorities receive automatically generated reports that they use a) to evaluate the functioning of the system, b) to make evidence-based decisions and c) to develop and implement necessary measures with the objective of meeting water protection targets."

often insufficient, which explains why authorities get into difficulties concerning time and workload management when it comes to the regular evaluation of data.

For the measurement and calibration of the condition *lack of resources* (LACKRES), we solely consider personnel capacities within the sub-state authority. Due to limited data availability on financial resources, we do not explicitly include them. To calibrate this condition, we use a combination of the number of employees in the responsible division of urban water management in each sub-state authority as well as the number of municipalities in each sub-state. We assume that by dividing the percentage of full-time job positions by the number of municipalities, we can provide a relative estimate of organizational capacities (*OC*). For instance, sub-states with many municipalities (e.g. BE (351 municipalities), ZH (168)) generally require more employees to fulfill the same tasks as sub-states with less municipalities (e.g. GL (3), NW (11)). The cross-over point of 0.5 is fixed for an *OC* ratio of 2.0, which is mainly chosen based on the sample distribution. The value of 0.5 could, for instance, be generated if a case features one full-time employee (or a 100 percent full-time position) who is responsible for 50 municipalities, solely in terms of urban water management. Set membership scores for LACKRES are assigned in the following scheme: full set non-membership (0.0) for an *OC* ratio > 4, full set membership (1.0) for an *OC* ratio < 1.

Condition 3: Lack of digitalization culture (LACKDIGI)

To complement quantitative aspects of available resources at the organizational level, we additionally include a more qualitative factor, i.e. the digitalization culture in the sub-state, as a further condition influencing data evaluation. As suggested by both the literature as well as our exploratory interviews, a respective innovation culture is essential for successful initiatives of big data utilization (Surbakti et al. 2019; Marshall et al. 2015).

To operationalize the condition of a *lack of digitalization culture* (LACKDIGI) in the sub-state authority, we rely on a digitization index as calculated by Schmid et al. (2018) for Switzerland's sub-state authorities. The index includes variables on e-governance, e-voting and specific online services (Schmid et al. 2018). Thereby, it describes how engaged the sub-state authority is in adopting digital innovations within their service provision and indicates the general attitude towards digitalization among public actors. The measurement of the condition LACKDIGI corresponds to Schmid et al. (2018) digitization index which varies between values of 1.88 and -2.08. In the process of fuzzy-set calibration, a cross-over point at value 0.5 is defined based on the distribution of index values. Full set non-membership score (0.0) is assigned to digitization index values > 1, full set membership score (1.0) to values < -1. Further choices for fuzzy-set anchors are derived from the distribution of index values.

Condition 4: Administrative fragmentation (FRAG)

Our insights from exploratory expert interviews suggest that one of the most important factors on the institutional level is administrative fragmentation. Higher administrative fragmentation stands for increased variety in size and number of municipalities. This higher fragmentation increases transaction costs (Lubell et al. 2017) of exchanging and jointly evaluating data among local municipalities and sub-state authorities. We rely on this specific factor in order to represent how institutions can create barriers to innovation and digital transformation.

In Switzerland, the operation of the majority of sewer systems lies in the hand of 2'222 municipalities (BFS 2018). However, sub-states differ strongly in terms of number of municipalities within their jurisdictions. The condition a*dministrative fragmentation* (FRAG) is operationalized based on the number of municipalities N_{mun} in a given sub-state. With respect to the variable distribution, we employ fuzzy-set scores in the following logic. A sub-state with a comparatively small N_{mun} is regarded as highly centralized in its administration, and hence not fragmented at all. A full set non-membership score (0.0) is therefore assigned to $N_{mun} \leq 25$. In contrast, a sub-state with many municipalities is presumably strongly fragmented regarding its administration. Thus, the full set membership score (1.0) is given to $N_{mun} > 250$. In the sub-state BE, the maximum number of municipalities ($N_{mun,\ \max} = 351$) is reached. The cross-over point (0.5) is chosen for $N_{mun} = 60$, based on the variables' distribution. Further differentiating fuzzy-set scores can be found in Table 1.

Table 1: Calibration of outcome and conditions

	Explanation	**Measurement**	**Operationalization**
NO-EVA	Frequency of data evaluation on the performance of sewer systems by the division of urban water management in a sub-state authority	Ordinal variable: “How often is monitoring data evaluated by the sub-state authority?” - no data evaluation - incident-based data evaluation - periodic data evaluation - incident-based and periodic data evaluation	Manual fuzzy-set membership scores: *0:* periodic data evaluation and after relevant incident *0.33:* periodic data evaluation *0.67:* incident-based data evaluation *1:* no data evaluation
LACKVIS	Lack of vision of the individual representative in the division of a sub-state authority	Ordinal variable: “Is the sub-state representative agreeing to a possible future digital scenario?” - agreement to vision - agreement under precondition - disagreement to vision	Manual fuzzy-set membership scores: *0:* agreement to vision *0.4:* agreement under preconditions *1:* disagreement to vision
LACKRES	Lack of (human) resources in the division of a sub-state authority	Organizational capacities (OC) are measured by the percentage of full-time jobs [%] in the authority’s division of urban water management divided by the number of municipalities in each sub-state $OC = \frac{\text{Full-time jobs [\%]}}{N_{municipalities}}$	Manual fuzzy-set membership scores: *0:* $OC > 4$ *0.33:* $2 < OC \leq 4$ *0.67:* $1 \leq OC \leq 2$ *1:* $OC < 1$
LACKDIGI	Lack of digitalization culture in a sub-state authority	Schmid et al. (2018) provide an index on the digitization of Swiss sub-state authorities D_{index}	Manual fuzzy-set membership scores: *0:* $D_{index} > 1$ *0.33:* $0.5 < D_{index} \leq 1$ *0.67:* $-1 < D_{index} \leq 0.5$ *1:* $D_{index} \leq -1$
FRAG	Administrative fragmentation in a sub-state	Administrative fragmentation is measured by the number of municipalities N_{mun} in a sub-state	Manual fuzzy-set membership scores: *0:* $N_{mun} \leq 25$ *0.2:* $25 < N_{mun} \leq 50$ *0.4:* $50 < N_{mun} \leq 75$ *0.6:* $75 < N_{mun} \leq 150$ *0.8:* $150 < N_{mun} \leq 250$ *1:* $N_{mun} > 250$

5. Analysis and results

Table 2 presents the truth table for the outcome NO-EVA, that is, the fact that sub-states do not evaluate data on the performance of sewer systems. The combination of four conditions results in 16 possible configurations, from which 11 are empirically observed in the dataset and appear in Table 2 (that is, 11 configurations have empirically observed cases that are strong members in the respective set). This leaves us with 5 logical remainders that are not displayed in the truth table. We set the threshold for configurations consistently leading to the outcome at 0.9, which corresponds to a major gap in consistency scores and separates configurations covering cases that show the outcome from configurations covering cases that do not show the outcome. Two exceptions are SH, covered by a configuration non-sufficient for the outcome even though being a strong member in the outcome, and VS, covered by a configuration sufficient for the outcome even though not being a member in the set of cases with the outcome. The last truth table column lists the empirical cases. Given that the analysis focuses on barriers, we only present and discuss results for the outcome NO-EVA, and refer to Appendix B for a presentation of results for sub-states where data is actually evaluated (no-eva[3]). For NO-EVA, the analysis of necessity reveals that there is no individually necessary condition (see Table B.1 in Appendix B).

[3] Conditions and outcome written in lowercase letters stand for their absence, in uppercase letters for their presence.

Table 2: Truth table for the analysis of sufficiency for NO-EVA

LACKVIS	LACKRES	LACKDIGI	FRAG	**NO-EVA**	Consistency	PRI	Cases
0	1	0	1	1	1.00	1.00	BE, SO
0	1	0	0	1	1.00	1.00	NE
1	1	1	0	1	1.00	1.00	AR
1	1	1	1	1	1.00	1.00	GR
1	0	1	0	1	0.99	0.97	OW, UR
0	1	1	0	1	0.98	0.96	JU
1	1	0	1	1	0.96	0.93	AG, SG
0	1	1	1	1	0.95	0.93	BL, FR, LU, TI, TG, VD, VS
0	0	1	1	1	0.91	0.80	ZH
0	0	1	0	0	0.86	0.67	GL, SH, SZ
0	0	0	0	0	0.70	0.33	NW, ZG

PRI = proportional reduction in inconsistency
Raw consistency threshold: ***0.9***

The configurational information in the truth table is then subjected to the Quine-McCluskey algorithm, which returns different logical solution terms that vary in their complexity, depending on how they take configurations without information on the consistency for the outcome into account (Schneider and Wagemann 2012). We restrict the presentation of results to the intermediate solution which is equivalent to the parsimonious solution (see Table 3). The conservative solution is listed in Table B.4 in Appendix B.

Table 3: Intermediate (and parsimonious) solution

Solution term	**LACKVIS** +	**LACKRES** +	**FRAG** →	**NO-EVA**
Single case coverage	OW, UR; AG, SG; AR, GR	NE; BE, SO; JU; BL, FR, LU, TI, TG, VD, VS; AG, SG; AR; GR	ZH; BE, SO; BL, FR, LU, TI, TG, VD, VS; AG, SG; GR	
Consistency	0.96	0.92	0.91	
Raw coverage	0.58	0.70	0.55	
Unique coverage	0.16	0.08	0.04	
Solution consistency				**0.91**
Solution coverage				**0.91**

The raw consistency threshold was set at 0.9. Number of multiple-covered cases is 13.
Directional expectations are LACKVIS → NO-EVA; LACKRES → NO-EVA; LACKDIGI → NO-EVA; FRAG → NO-EVA.

The solution consists of three alternative individual conditions sufficient for the non-evaluation of data.[4] The consistency and coverage scores express to what extent statements about set-theoretic relations between conditions and the outcome are supported by empirical evidence. An overall consistency score of 0.91 indicates that the solution is consistent with empirical evidence from the cases to a very large degree. An overall coverage value of 0.91 means that 91% of the outcome values are covered by the solution formula. 13 out of 18 cases are covered by more than one of the three conditions. The case labels appear in the table together with each solution. Robustness of a) the fuzzy-set values to the exact calibration procedure and b) results to small changes in the calibration procedure and fuzzy-set values is discussed in Appendix D. The findings show that sub-states where individual representatives of the sub-state authority lack vision (first term), or that are lacking resources (second term), or are confronted with a fragmented administrative structure (third term) are very likely to not evaluate data. In the

[4] In the Table, + represents logical 'or.'

following, we interpret each solution with insights of case knowledge in order to complement and validate the results of the comparative analysis.

A first solution term for why sub-states do not evaluate data is given by the condition of a lack of vision at the individual level (LACKVIS) and covers six sub-states. Half of the six sub-states covered by this solution, OW, UR, AR, are some of the smallest sub-states of Switzerland by size and population. Indeed, digital transformation can have more relevance and value for larger sewer networks, as stated by the sub-state representative of AR. Size could thus partially correlate with a lack of vision at the individual level, potentially due to reduced professionalism and missing awareness for the necessity of evaluating data. However, according to the configurational nature of our approach, this is not the only important factor, given that another small sub-state (NW) is actually the most progressive regarding evaluating data from sewer systems.

The second solution term (LACKRES) demonstrates that in most sub-state authorities (15 out of 18), personnel resources are not available in order to evaluate data from sewer systems. Thus, even though a vision for digital transformation of urban water management may be present, evaluation of data fails due to the unavailability of sufficient organizational capacities, i.e. human resources, at the level of the sub-state authority. For instance, the sub-state SO is generally very innovative and one of the most motivated sub-states in Switzerland when it comes to digitalization of urban water management. Since 2017, SO provides an online database where information on specific infrastructure elements is stored and openly available. In addition, together with the sub-state BE, SO created a digital data management concept to build up necessary IT infrastructures for a smarter management of sewer systems in the future. However, even though innovativeness and vision are clearly present, the sub-states SO and BE do not have sufficient personnel to evaluate data from sewer systems on a regular basis. In the sub-state TG, the situation is similar: though their openness towards digitalization is comparatively high (e.g., they conducted a survey on sewer data management among their municipalities in 2017), organizational capacities at the authority's level are lacking. In the sub-state GR, the division representative himself expressed his concern about the lack of human resources.

The third solution term (FRAG) suggests that strong administrative fragmentation also plays a role for the absence of data evaluation. This condition can explain the absence of data evaluation in 13 sub-states. We can see that several sub-states that are struggling with a lack of resources (i.e., second solution) are also listed for the third solution term (e.g. BE, SO and ZH), suggesting that resources are especially key if administrative fragmentation is high, and coordination is needed with a large number of municipalities. Overall, BE is the most fragmented sub-state in Switzerland when it comes to administration. Evaluating data from more than 300 municipalities is presumably very time consuming and not achievable with current personnel in the sub-state authority. This shows that the institutional environment as a contextual precondition influences transaction costs, meaning that sub-states that are naturally challenged by fragmented administration do have a disadvantage when it comes to the efforts of evaluating data.

6. Discussion

Based on the literature on digital transformation, big data utilization and organizational innovation as well as case knowledge and insights from expert interviews, we have tested the joint influence of four different factors as hindering data evaluation by public authorities. Potential barriers stem from individual, organizational and institutional levels. The analysis reveals that conditions at all three levels affect data utilization in alignment with our expectations – their presence hinders data evaluation. As a consequence, the combination of conditions from multiple levels are required for the opposite outcome, that is, the evaluation of data (see Table B.3 in Appendix B). The analysis reveals that authorities having a vision at the individual level (lackvis), having sufficient resources at the organizational level (lackres) and not being confronted with administrative fragmentation (frag) do manage to evaluate data.

This finding implies that digital transformation is not easy to achieve: the utilization of data may fail if only one condition is absent, but may only be successful if all conditions are present. Yet, there is also a more optimistic interpretation of our results: the barrier with the highest coverage value, which also acts as an explanation for 15 out of 18 cases where data is not evaluated – a lack of resources at the organizational level – might be the one that is easiest to change for sub-state authorities. By contrast, lack of vision at the individual level or administrative fragmentation are likely barriers that are more difficult to work on for sub-state authorities.

While previous studies have also identified several factors from different levels to be important (Sun et al. 2016; Surbakti et al. 2019; Tornatzky et al. 1990), our work has further elucidated the effect of these factors as conditions sufficient for the occurrence of the outcome. Based on a mix of deductive and inductive logics, that is, theoretical insights and in-depth case knowledge, we identify barriers at three different levels. However, there may be other factors potentially influencing the evaluation of data. For example, besides the vision of the individual responsible for data evaluation at the sub-state authority, the actual data science expertise of the sub-states' representatives might matter (Klievink et al. 2016). Taking organizational resources into account, we incorporated this factor to some degree – assuming that personal skills can be acquired through financial and personnel resources.

Furthermore, we have analyzed public actors at the level of sub-states, which includes public authorities at the level of the sub-state government, but also municipalities and other public operators of sewer systems. Whereas sub-state authorities can install strong incentive structures and provide knowledge, data evaluation is at the end a joint task of these actors. Disentangling the network structures among different actors concerned by the challenge of digital transformation would be the task of future studies. Also, other potentially important actors are other political entities acting as role models, as argued by the literature on innovation diffusion (Rogers 2003; Shipan and Volden 2008). Individual case studies of most interesting cases could help in disentangling the more detailed mechanisms and processes over time that are responsible for why sub-states do or do not evaluate data.

To better understand existing barriers, two perspectives appear to be relevant for future research endeavors. First, barriers to the digital transformation need to be identified at other actor levels, e.g. operators and utilities. Second, adopting a network approach allows to investigate relational barriers between actor levels that are hindering the exchange of data and, overall, the progress of digital transformation. Both perspectives in combination can provide insights for further research questions which also should address the development of feasible solutions on how to overcome existing barriers.

7. Conclusion

The digital transformation of infrastructure sectors could result in higher efficiency and more opportunities for evidence-based decision-making, especially in urban water management where only little is known on the performance of sewer systems (Fletcher and Deletic 2007). However, exploiting the full value of data is hindered by different barriers (Shearmur and Poirier 2016, Wang and Feeney 2014; Hoppe et al. 2019). This article focuses on digital transformation in the public sector, by studying the barriers to data utilization related to the performance of urban wastewater infrastructures in Swiss sub-states. We found evidence of hindering factors at individual, organizational and institutional levels.

Our analysis contributes to the study of digitalization in organizations by elucidating barriers to utilizing data. We have aimed at explaining a specific outcome – why sub-states do not evaluate data from sewer systems. This is an important outcome, as digitalization per se does often not provide immediate benefits, but rather produces large amounts of data leading to data wasting (Mergel et al. 2016), if not shared, treated and analyzed accordingly (Sun et al. 2016). On the side of explanatory factors – barriers to data utilization – this article proposes a quite generic model, based on an interdisciplinary review of relevant literature as well as insights from practice. Although we cannot make strong claims about the generalizability of the specific solutions, the analytical approach that we propose is applicable to many different infrastructure sectors and the study of digital innovation – or the lack thereof – in these sectors, as well as in many different political contexts.

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Appendix

Appendix A: Sub-states of Switzerland, raw data and fuzzy-set scores

Table A.1: Sub-states of Switzerland and their abbreviations (case IDs)

	Name of sub-state
AG	Argovia
AI*	Appenzell Inner-Rhodes
AR	Appenzell Outer-Rhodes
BE	Berne
BL	Basle-Country
BS*	Basle-City
FR	Fribourg
GE*	Geneva
GL	Glarus
GR	Grisons
JU	Jura
LU	Lucerne
NE	Neuchâtel
NW	Nidwald
OW	Obwald
SG	St. Gall
SH	Schaffhouse
SO	Solothurn
SZ	Schwyz
TG	Thurgovia
TI	Ticino
UR	Uri
VD	Vaud
VS	Valais
ZG	Zoug
ZH	Zurich

* We exclude sub-states AI, BS and GE from the analysis as in these sub-states, the authority itself operates most parts of the sewer system.

Table A.2: Raw data matrix

Case	Outcome: **NO-EVA** *Data evaluation*	Condition: **LACKVIS** *Vision*	Condition: **LACKRES** OC	Condition: **LACKDIGI** D_{index}	Condition: **FRAG** N_{mun}
AG	1	0	0.94	1.38	213
AR	0	0	0.75	-1.09	20
BL	1	1	1.74	-1.09	86
BE	0	1	1.28	0.89	351
FR	1	0.5	1.10	-0.85	136
GL	2	0.5	6.67	-0.10	3
GR	0	0	1.79	-0.60	112
JU	0	0.5	1.75	-0.10	57
LU	0	0.5	1.69	0.39	83
NE	1	0.5	1.39	1.38	36
NW	3	1	4.55	0.64	11
OW	0	0	3.57	0.14	7
SH	1	0.5	7.69	-0.10	26
SZ	1	0.5	3.33	-0.60	30
SO	0	1	0.92	0.64	109
SG	0	0	1.17	1.88	77
TI	1	0.5	1.74	-1.09	115
TG	1	0.5	1.25	0.39	80
UR	0	0	2.50	-1.59	20
VD	0	0.5	1.29	-1.09	309
VS	2	1	0.20	-2.08	126
ZG	2	1	9.09	1.38	11
ZH	2	1	2.38	0.39	168

Key of case IDs: Abbreviations for sub-states in Switzerland

Data stems from semi-structured interviews in October 2017, BFS (2018) and Schmid et al. (2018).

Table A.3: Fuzzy-set scores

Case	Outcome: **NO-EVA**	Condition: **LACKVIS**	Condition: **LACKRES**	Condition: **LACKDIGI**	Condition: **FRAG**
AG	0.67	1	1	0	0.8
AR	1	1	1	1	0
BL	0.67	0	0.67	1	0.6
BE	1	0	0.67	0.33	1
FR	0.67	0.4	0.67	0.67	0.6
GL	0.33	0.4	0	0.67	0
GR	1	1	0.67	0.67	0.6
JU	1	0.4	0.67	0.67	0.4
LU	1	0.4	0.67	0.67	0.6
NE	0.67	0.4	0.67	0	0.2
NW	0	0	0	0.33	0
OW	1	1	0.33	0.67	0
SH	0.67	0.4	0	0.67	0.2
SZ	0.67	0.4	0.33	0.67	0.2
SO	1	0	1	0.33	0.6
SG	1	1	0.67	0	0.6
TI	0.67	0.4	0.67	1	0.6
TG	0.67	0.4	0.67	0.67	0.6
UR	1	1	0.33	1	0
VD	1	0.4	0.67	1	1
VS	0.33	0	1	1	0.6
ZG	0.33	0	0	0	0
ZH	0.33	0	0.33	0.67	0.8

Key of case IDs: Abbreviations for sub-states in Switzerland

Fuzzy-set scores are based on the calibration procedure of the individual conditions and the outcome as shown in Table 1.

Appendix B: Analysis of Necessity and Solution Terms

Analysis of Necessity

The analysis of necessity compares one condition and the outcome in terms of set membership scores. For a condition to be ‘necessary’, its set membership requires to be larger or equal to the set membership of the outcome, across all empirical cases. In the following tables, we provide an overview on resulting parameters for the analysis of necessity that are:

- **Consistency of necessity** states whether the presence of the outcome implies the presence of the condition. The parameter is calculated by $Y_i \leq X_i = \sum(\frac{\min(X_i,Y_i)}{\sum Y_i})$.
- **Coverage of necessity** expresses the empirical importance of a condition for explaining the outcome, i.e. measures how much of the outcome is covered by the condition. The parameter is calculated by $Y_i \leq X_i = \sum(\frac{\min(X_i,Y_i)}{\sum X_i})$.
- **Relevance of necessity (RoN)** indicates whether a condition is trivial or relevant. The parameter is calculated by $\frac{\sum(1-X_i)}{\sum(1-\min(X_i,Y_i))}$.

Table B.1: Results of the analysis of necessity for the occurrence of the outcome (NO-EVA)

Condition	**Consistency**	**Coverage**	**Relevance of Necessity (RoN)**
LACKVIS	0.58	0.96	0.97
LACKRES	0.70	0.92	0.91
LACKDIGI	0.68	0.83	0.80
FRAG	0.51	0.91	0.94
lackvis	0.56	0.72	0.74
lackres	0.44	0.71	0.81
lackdigi	0.44	0.79	0.87
frag	0.61	0.79	0.78

No individual condition is meeting the thresholds for consistency (0.9), coverage (0.5) and relevance (0.5), thus there is no single necessary condition for the outcome NO-EVA.

Note that a condition written in uppercase letters marks its presence, in lowercase letters its absence.

Table B.2: Results of the analysis of necessity for the non-occurrence of the outcome (no-eva)

Condition	Consistency	Coverage	Relevance of Necessity (RoN)
LACKVIS	0.43	0.27	0.64
LACKRES	0.52	0.26	0.52
LACKDIGI	0.68	0.32	0.50
FRAG	0.56	0.35	0.67
lackvis	0.94	0.46	0.59
lackres	**0.84**	**0.52**	**0.72**
lackdigi	0.63	0.43	0.72
frag	0.86	0.42	0.57

Necessary conditions meeting the thresholds for consistency (0.7), coverage (0.5) and relevance (0.5). Thus, lackres (in bold) is a necessary condition for the non-occurrence of the outcome no-eva.

Note that a condition written in uppercase letters marks its presence, in lowercase letters its absence.

Analysis of Sufficiency

The analysis of sufficiency follows the analysis of necessity. The heart of the analysis is the so-called 'truth table' that we present and explain in detail within the text. For each row in the truth table (a 'configuration'), the following parameters describe the measures of fit:

- **Consistency** measures to which degree a condition is a subset of the outcome. The parameter is calculated by $X_i \leq Y_i = \sum(\frac{\min(X_i,Y_i)}{\sum X_i})$.
- **Proportional Reduction in Inconsistency (PRI)** indicates to which degree a condition is a subset of the occurrence of the outcome rather than a subset of the non-occurrence of the outcome. The parameter helps to identify whether the condition is sensitive to being a subset of the occurrence of the outcome and the non-occurrence thereof. It is calculated by $\frac{\sum \min(X_i,Y_i)-(\min(X,Y,1-Y)}{\sum \min(X_{i,})-(\min(X,Y,1-Y)}$.
- **Raw coverage** expresses how much of the outcome is covered by each solution path. The parameter is calculated by $X_i \leq Y_i = \sum(\frac{\min(X_i,Y_i)}{\sum Y_i})$.

- **Unique coverage** states how much of the outcome is covered by only one specific solution path.
- **Solution consistency** measures to which degree the solution path is sufficient for explaining the outcome.
- **Solution coverage** measures how much of the outcome is covered by the entire solution term.

Configurations that pass specified thresholds are then subjected to the Quine-McCluskey algorithm that returns configurations in three types of solutions:

- **Conservative (or complex) solution** includes only configurations that are empirically observed. No assumptions are made about any logical remainders, that is, logical configurations that are not covered by empirical cases.
- **Intermediate solution** considers logical remainders only if they correspond to the assumptions ('directional expectations') as defined by the researcher. In terms of complexity, the solution lies in-between conservative and parsimonious solutions.
- **Parsimonious solution** takes into account assumptions about logical remainders in order to return a solution term with the minimum of conditions (least complex solution).

Solution Terms

Table B.3: Conservative, parsimonious and intermediate solution for the non-occurrence of the outcome (no-eva)

Solution term	**lackvis * lackres * frag**	**→**	**no-eva**
Single case coverage	NW, ZG; GL, SH, SZ		
Consistency	0.76		
Raw coverage	0.76		
Unique coverage	-		
Solution consistency			**0.76**
Solution coverage			**0.76**

The raw consistency threshold was set at 0.7. Number of multiple-covered cases is 0.

Table B.4: Conservative solution for the occurrence of the outcome (NO-EVA)

Conservative Solution	LACKRES*lackvis +	LACKRES*FRAG +	LACKDIGI* lackvis*FRAG +	LACKDIGI*LACKVIS*frag	→ NO-EVA
Single case coverage	NE; BE, SO; JU; BL, FR, LU, TI, TG, VD, VS	BE, SO; BL, FR, LU, TI, TG, VD, VS; AG, SG; GR	ZH; BL, FR, LU, TI, TG, VD, VS	OW, UR; AR	
Consistency	0.92	0.95	0.90	0.99	
Raw coverage	0.45	0.50	0.34	0.37	
Unique coverage	0.10	0.09	0.00	0.20	
Solution consistency					**0.91**
Solution coverage					**0.78**

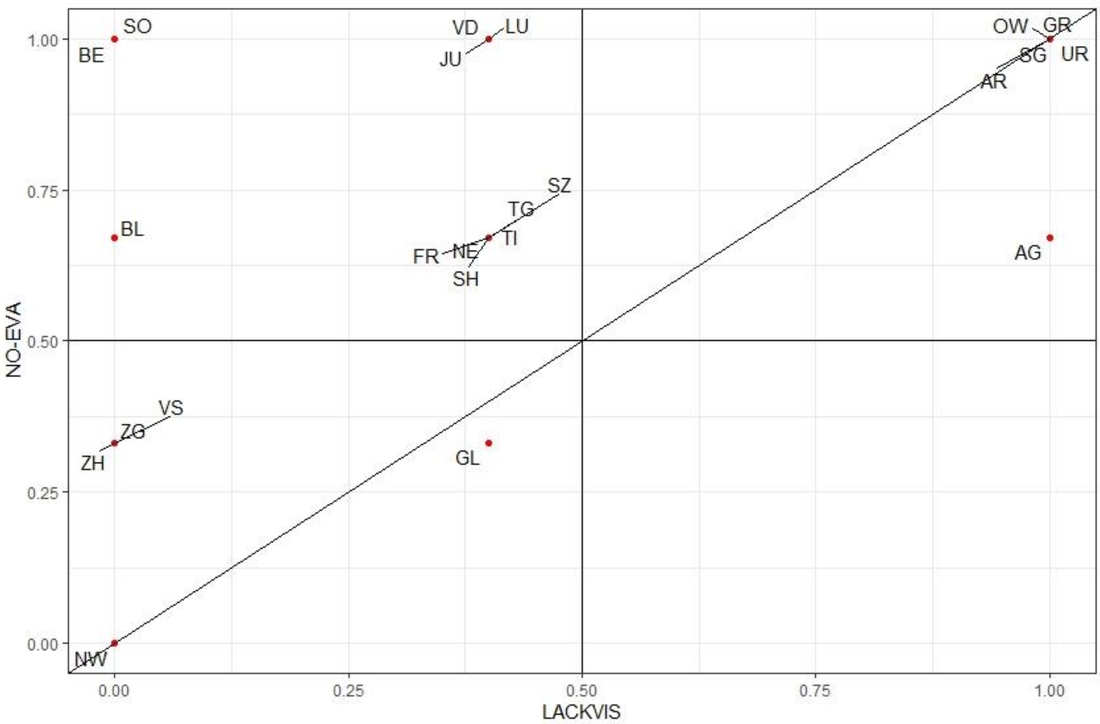
The raw consistency threshold was set at 0.9. Number of multiple-covered cases is 9.

Appendix C: Visual interpretation of the relation between conditions and outcome

The following Figures C.1 to C.4 present plots of fuzzy-set scores of each individual condition and the outcome NO-EVA. This form of visualization allows to make additional interpretations to those in Appendix B on necessity and sufficiency.

When taking a look at the upper left quadrant in Figure C.1, we observe many empirical cases where the condition LACKVIS is not present (below the cross-over point of 0.5) yet the outcome NO-EVA occurs (e.g. cases BE, SO, BL, LU, etc.). This is contradictory to our assumption that LACKVIS is necessary for the outcome NO-EVA, which makes the cases in the upper left quadrant so-called “deviant cases inconsistent in degree”. For the analysis of sufficiency, we consider the lower right quadrant where no case is plotted. NO-EVA is not observed, if LACKVIS is not present. Thus, in terms of sufficiency, we do not have any “deviant case inconsistent in degree”. Only the case AG can be classified as a “deviant case inconsistent in kind”, as the fuzzy-set score of NO-EVA is lower than the one of LACKVIS.

Fig. C.1: Condition LACKVIS and outcome NO-EVA



Interpretations for Figures C.2 to C.4 can be carried out in the same way as explained above. Figure C.2 illustrates that the four cases SH, SZ, OW, UR are “deviant cases inconsistent in degree” when it comes to the necessity of LACKRES for NO-EVA. In terms of sufficiency, the case VS represents such a deviant case. Even though resources are lacking (LACKRES), the sub-state authority evaluates data (no-eva).

Fig. C.2: Condition LACKRES and outcome NO-EVA

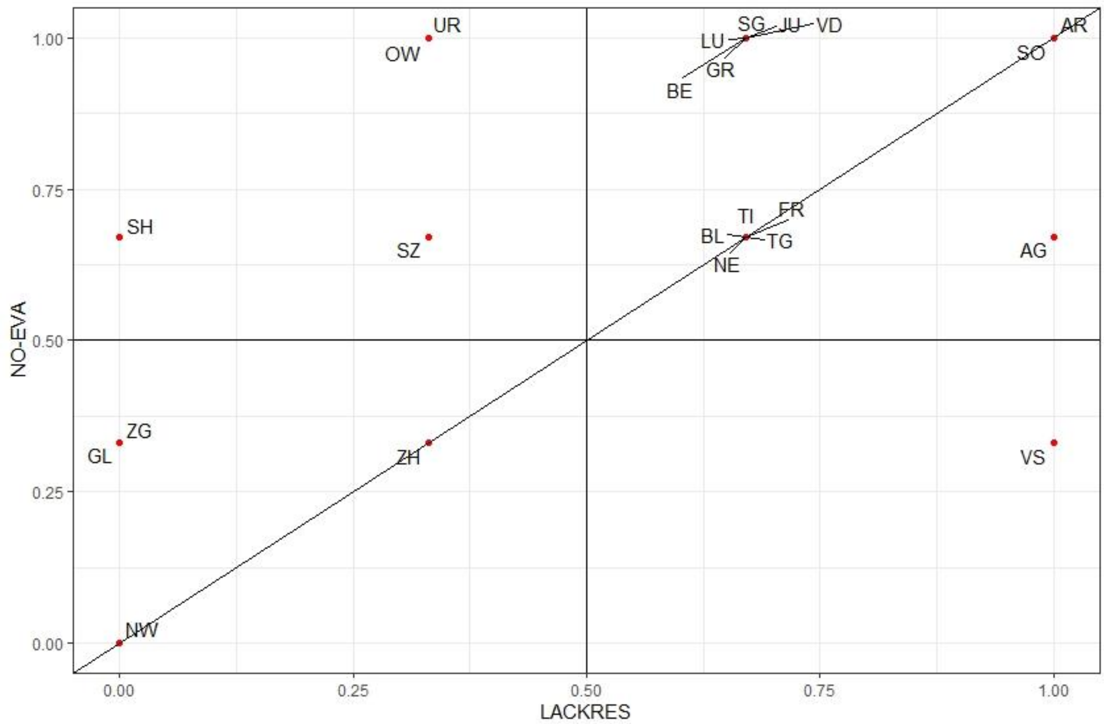


Figure C.3 shows that five cases SG, SO, BE, AG, NE are “deviant cases inconsistent in degree” regarding the necessity of LACKDIGI for NO-EVA. In these sub-states, even though data is not evaluated (NO-EVA), a digitalization culture is not lacking (lackdigi) at the organizational level. Regarding sufficiency, the cases ZH, GL and VS represent such deviant cases.

In Figure C.4, seven cases are “deviant cases inconsistent in degree” regarding the necessity of FRAG for NO-EVA. In these sub-states, data is not evaluated (NO-EVA) while they are not administratively fragmented (frag). For the analysis of sufficiency, the cases ZH and VS are "deviant cases inconsistent in degree".

Overall, these findings are in line with the calculated parameters of fit in Appendix B.

Fig. C.3: Condition LACKDIGI and outcome NO-EVA

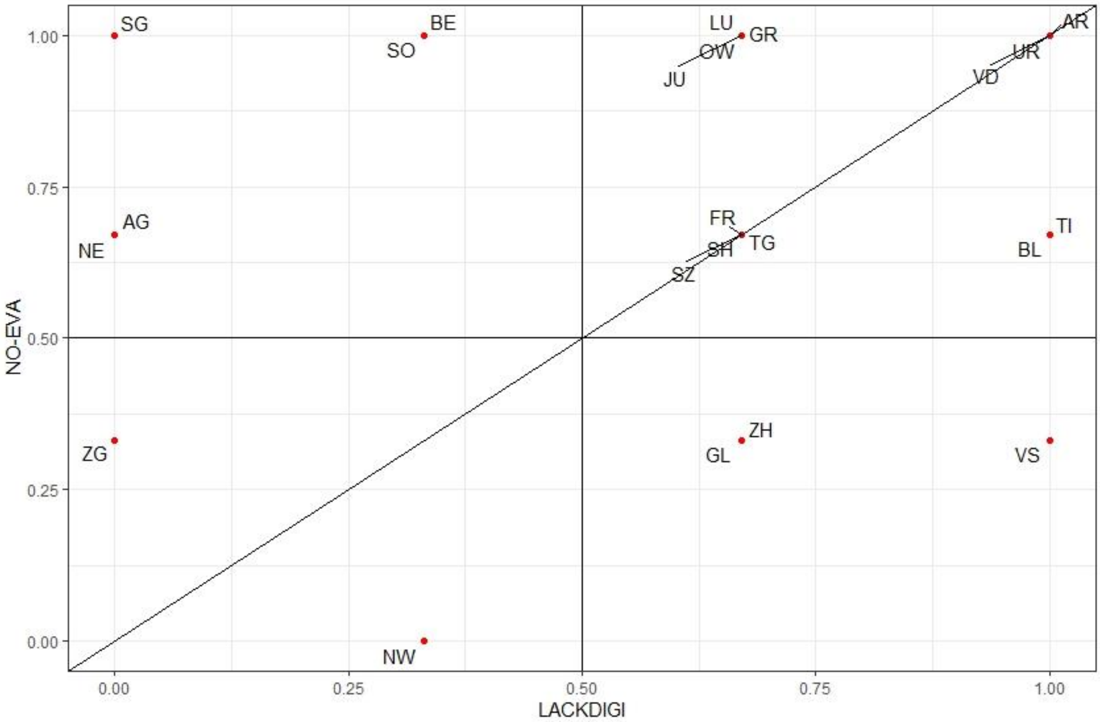
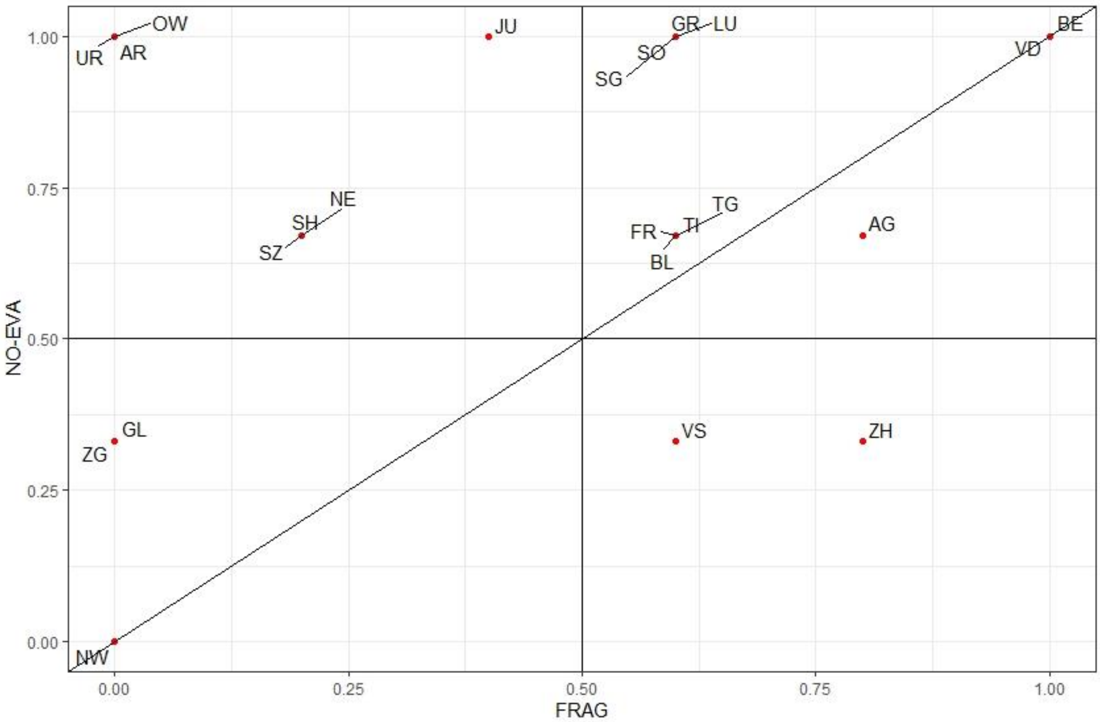


Fig. C.4: Condition FRAG and outcome NO-EVA



Appendix D: Robustness tests

Robustness tests serve to assess the sensitivity of QCA results. Skaaning (2011) suggests to focus on three aspects: i) calibration of fuzzy-set membership scores from raw data, ii) empirical evidence in terms of frequency of cases linked to the configurations, and iii) choice of raw consistency thresholds. In the following, we reflect upon the robustness of our analysis and obtained results.

First, we used the method of direct calibration for assigning fuzzy-set membership scores for each condition and the outcome. All anchors, including the cross-over point, were defined by both taking into account logical considerations, case-specific knowledge and the distribution of raw data values. For instance, the outcome NO-EVA is based on an interval-scaled variable with logically equal distances, which makes our choice on its calibration comprehensible. Therefore, we claim that the calibration procedure that we followed is reasonably robust.

Second, the truth table (Table 2) suggests that 11 out of 16 possible configurations are empirically observed with varying number of cases per configuration. In the solution (Table 3), however, many cases provide evidence for respective solution terms.

Third, the choice of raw consistency threshold (0.9) in the analysis of sufficiency for the outcome NO-EVA is based on two considerations: on the one hand, it corresponds to a major gap in consistency scores, on the other hand it separates configurations covering cases that show the occurrence of the outcome NO-EVA from configurations covering cases that do not show the outcome. Even if we set the raw consistency threshold at a higher value of 0.95, the solution paths of the intermediate solution (Table 3) remain the same. Consequently, we can conclude that our choice of the raw consistency threshold is comparatively robust.