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Technological frames in public administration: What do public managers think of big data?

Ali A. Guenduez[a,*], Tobias Mettler[b], Kuno Schedler[a]

[a] Smart Government Lab, Institute for Systemic Management and Public Governance, University of St. Gallen, Dufourstrasse 40a, 9000 St. Gallen, Switzerland
[b] Swiss Graduate School of Public Administration (IDHEAP), University of Lausanne, Rue de la Mouline 28, 1022 Chavannes-près-Renens, Switzerland

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ABSTRACT

Being among the largest creators and gatherers of data in many countries, public administrations are looking for ways to harness big data technology. However, the de facto uses of big data in the public sector remain very limited. Despite numerous studies aiming to clarify the term *big data*, for many public managers, it remains unclear what this technology does and does not offer public administration. Using the concept of *technological frames*, we explore the assumptions, expectations, and understandings that public managers possess in order to interpret and make sense of big data. We identify nine big data frames, ranging from inward-oriented techno-enthusiasts to outward-oriented techno-skeptics, each of which characterizes public managers' specific viewpoints relating to the introduction of big data in public administrations. Our findings highlight inconsistencies between different perceptions and reveal widespread skepticism among public managers, helping better understand why the de facto uses of big data in the public sector remain very limited.

1. Introduction

Since the 1970s, many researchers have promoted the idea that public administration will undergo a data revolution, which will fundamentally reshape governmental structures, processes, and tasks (Shuman, 1975). Half a century later, after witnessing the IT productivity paradox (Brynjolfsson, 1993; Willcocks & Lester, 1996) and the e-government crisis (Sorrentino & De Marco, 2013), the same vision is heralded again: big data is now the hope for effective and efficient government decision-making and action (Fantuzzo & Culhane, 2016; Kitchin, 2014). Numerous efforts have been made to make big data fruitful for public administration: the term has been defined conceptually for public administration (Mergel, Rethemeyer, & Kimberley, 2016), possible use cases have been identified (Chan & Moses, 2017; Kim, Trimi, & Chung, 2014), and big data's perils and potentials for the public sector have been discussed (Bollier & Firestone, 2010; Desouza & Jacob, 2017). However, as Klievink et al. (2017, p. 268) noted, the de facto uses of big data in the public sector remain very limited. The authors suspect "that government organizations are postponing decisions on big data use because they are unsure… whether and how to implement big data, and they lack the tools to determine if they are ready for big data use". We concur, and suspect that public organizations' uncertainty about whether and how to implement big data arises from public managers' very different opinions, expectations, assumptions, and understandings about uses of big data in public administrations. Today, we see confusion rather than a streamlined vision, and disorientation instead of coordinated actions (Bollier & Firestone, 2010). Different understandings and expectations of what big data could potentially do (and what not to do) to improve government services is problematic and could lead to possible over-estimations or under-estimations of its potential impacts (Nickerson & Rogers, 2014). Different understandings further pose a major challenge for defining organizational and technical standards and make it hard to agree on a shared vision or future roadmap for the use of big data in public administrations, slowing the development of potentially valuable uses of big data.

Highlighting the perceptions and understandings of public managers can help one to better understand why the de facto uses of big data remain very limited in the public sector, since they provide important insights into how those responsible for implementing and using big data actually interpret and understand big data (Mergel, Kleibrink, & Sörvik, 2018). To date, public managers have been neglected in the literature. This is surprising, because a common source of failure in public IT projects is the lack of attention to understanding managers' cognitions as possible predictors of involvement and positive promotion for IT-induced change in public administrations (Khalil, Winkler, & Xiao, 2017; Lawry, Waddell, & Singh, 2007; Schedler, Guenduez, & Frischknecht, 2019). Research into the implementation of information

* Corresponding author.
E-mail address: aliasker.guenduez@unisg.ch (A.A. Guenduez).

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systems in the past decades has shown that managerial perceptions and interpretations influence investment in and adoption of new technologies. This is true for managers generally (Harrison, Mykytyn, & Riemenschneider, 1997; Leonardbarton & Deschamps, 1988) and for public managers in particular (Damanpour & Schneider, 2009; Gagnon, 2001; Ginsberg & Venkatraman, 1992). Studies have shown that even pre-adoption thoughts influence a technology's implementation. Ginsberg and Venkatraman (1992), for instance, showed that managers' perceptions and interpretations of an emerging technology for electronic filing of tax returns in 1987 predicted its adoption a year later. Similarly, using path analysis, Thomas, Clark, and Gioia (1993) showed that interpretation behaviors of hospital managers in 1987 predicted strategic changes in the following 3 years. These findings are of interest, because the de facto uses of big data in public administrations remain in their infancy (Kim et al., 2014), including in Switzerland (Jarchow & Estermann, 2015). Government organizations are still in an orientation or contemplation phase regarding big data's uses (Klievink et al., 2017). Thus, uncovering public managers' different beliefs and understandings about big data and comparing divergent mindsets may help us to better understand what is slowing down public administrations' implementing big data. We seek to explore public managers' *expectations, assumptions, and understandings* regarding the uses of big data in public administration. Different to studies designed to report sentiments as *composite average opinions*, we reveal *combinations of varying opinions* with the purpose of answering the following research question: *What affordances and constraints do public managers associate with the introduction and uses of big data in public administration?*

We use technological frames analysis (Orlikowski & Gash, 1994) as a theoretical lens to uncover public managers' underlying perceptions and assumptions relating to big data. This theoretical approach suggests that technology is cognitively embedded and that cognitive patterns influence individuals' acceptance of a technology. In this view, public managers' technological frames are cognitive structures around big data – their assumptions, beliefs, and expectations concerning big data's uses in public administration, i.e. how they make sense of big data. Inspired by Orlikowski and Gash's influential work, studies have shown that technological frames shape technology trajectories over the entire technology lifecycle (Davidson, 2002; Kaplan & Tripsas, 2008). They have also documented that the initial stage of framing a technology is most formative for its later use. Actors' differing technological frames in this stage are a critical source of technical variation. Depending on the frames used, people give a technology a certain meaning, affecting the paths it takes and whether or not it is adopted (Kaplan & Tripsas, 2008).

The remainder of this paper is structured as follows. In the next section, we review research into big data in the public sector. We then emphasize the importance of exploring public managers' cognitive structures underlying the big data concept, giving an overview of the few studies into this topic. We apply a mixed research approach called Q-methodology, widely used in previous studies to detect different technological frames relating to the implementation of various IT artifacts designed for and used in different domains or settings. Based on our interpretation of Q-methodology data, we then discuss our study's primary implications and conclude with a description of limitations and avenues for future research.

2. Literature review

2.1. Big data and the public sector

Before we investigate how public managers perceive big data, we clarify the term and review the literature into big data in public administrations. It is not easy to define big data. Ambiguities about the scope and disagreements about the character of big data have increased significantly (Ekbia et al., 2015; Chen, Chiang, & Storey, 2012). This also impacts the public sector. Confusing factors include not only *big*, which is relational, but also *data*, which is not absolute (Floridi, 2012). What is big today can be small tomorrow; what is not captured by sensors now can be available from new automatized data sources in the future. For this reason, Mergel et al. (2016) see big data as a "moving target" in the sense that "what is possible now is less than what will be possible in the future." Following Mergel and her coauthors, we define big data in public administrations as "high-volume data that frequently combines highly structured administrative data actively collected by public sector organizations with continuously and automatically collected structured and unstructured real-time data that are often passively created by public and private entities through their Internet interactions" (Mergel et al., 2016, p. 931).

There are several reasons why government organizations are postponing decisions about big data's uses. The literature on big data's dark side in public administrations reveals many potential perils of its uses in public administrations. First, there are concerns that the insights gained via big data can be misused (Schintler & Kulkarni, 2014). There are also uncertainties regarding privacy, access, and information policies, as well as how personal data are managed, curated, and preserved (McNeely & Hahm, 2014; Shilton, 2012). Loss of privacy, lack of access to data, poor information policies, and inappropriate handling of personal data can undermine trust in public authorities and can result in a loss of legitimacy. Thus, big data can be seen as a threat to citizens' privacy (Lane, Stodden, Bender, & Nissenbaum, 2014; Van Dijck, 2014) and thus as "a troubling manifestation of Big Brother, enabling invasions of privacy, decreased civil freedoms, and increased state and corporate control" (Boyd & Crawford, 2012, p. 664). China's Social Credit System, which rates the trustworthiness of its 1.3 billion citizens, is a well-known example of such use of big data in public administration. Researchers have also pointed to increased inequality; policies informed by big data are often biased and favor those who leave digital footprints, leaving those who are not online unheard (Heikkila & Isett, 2007). In other words, while public administrators may know too much about some people, they may know too little about others and, thus, may potentially make wrong decisions about what and how public programs and corresponding services should be provided.

These potential threats can, to some extent, explain why government organizations are unsure about whether or not to implement big data, and how. However, the literature on the upsides of big data in public administrations also holds promises that argue for its use. To start with, researchers suggest that big data can improve government-citizen understanding (Clarke & Margetts, 2014). The wealth of information and insights provided by big data enable public sector organizations to align their services with citizens' needs, towards the provision of person-centered services (Chen et al., 2012). Enhanced insights into citizens' needs also enable more informed public policy-making (Ho, 2017; Höchtl, Parycek, & Schöllhammer, 2016) and improve public programs' responsiveness (Mergel et al., 2016). Big data also provide comprehensive insights into the operation and performance of public organizations (Klievink et al., 2017), enable informed decision-making processes (Desouza & Jacob, 2017), and pave the way for evidence-based policymaking in public administrations (Bertot, Gorham, Jaeger, Sarin, & Choi, 2014; Ho, 2017; Höchtl et al., 2016). Researchers who highlight the upsides emphasize many application scenarios for big data in public administration, from public health (Alyass, Turcotte, & Meyre, 2015), to traffic (Lv, Duan, Kang, Li, & Wang, 2015), to public transportation (Zheng et al., 2016), to education (Daniel, 2015). Its application also offers new opportunities for monitoring and surveillance so as to improve public safety and security (Giest, 2017; Meijer & Thaens, 2013), as well as countering major challenges in the economy or natural disasters (Kim et al., 2014). All these studies assert that real-time, or near real-time data lead to more precise and comprehensive policies, whose outcome could even be predicted upfront (Janssen, van der Voort, & Wahyudi, 2017).

These two perspectives on big data reflect two opposing standpoints in the literature. There are reasons for and against using big data in public administrations. To some extent, the two perspectives explain the existing uncertainties and show the reasons why big data faces difficulties in the public sector. In our view, the expectations, assumptions, and understandings of public managers who implement big data in public administration can provide a much more precise understanding. As we will show, their perceptions are much more complex and multilayered, so it becomes crucial to take a close look at their technological frames. In the next two sections, we will explain this and will then move on to methodological analysis.

2.2. Applying technological frames for exploring managerial perceptions and understandings

For decades, researchers have paid attention to managerial cognition (Narayanan, Zane, & Kemmerer, 2011; Walsh, 1995). Many terms have been used in the literature to describe managers' cognitive structures, including “frame of reference” (March & Simon, 1958), “managerial perceptions” (Anderson and Paine, 1975), “interpretive schemes” (Greenwood & Hinings, 1988), “managerial thought structures” (Reger, 1990), “managerial lenses” (Miller, 1993), or “managers' subjective representations” (Nadkarni & Barr, 2008).

A number of scholars have adopted the cognitive perspective and have pioneered theoretical and empirical work into the links between managers' cognition and technology (Barley, 1986; Ginsberg & Venkatraman, 1992; Ginzberg, 1981). We focus on what Orlikowski and Gash (1994) call a “technological frame.” Frames are lenses through which actors process information and make decisions (Goffman, 1974). Confronted with a complex situation that lacks clear information and recognizable facts, individuals use frames to interpret and make sense of it. Frames help individuals deal with situations that are ambiguous, uncertain, and complex. Technological frames refer to a person's assumptions, knowledge, and expectations concerning individual, organizational, cultural, and ethical impacts of the introduction and uses of a certain technology.

Following Orlikowski and Gash (1994), how managers will implement and use technologies depend on how they understand and make sense of them. Scholars such as Kaplan and Tripsas (2008), Leonardi and Barley (2010), and many others (e.g., Benner & Tripsas, 2012; Elbanna & Linderoth, 2015; Griffith & Northcraft, 1996; Leonardi & Barley, 2010; Mettler & Wulf, 2018) who have reaffirmed and deepened Orlikowski and Gash's work on managers' cognition of new technologies. By adopting a cognitive perspective, they showed that technological frames call up different associations that lead managers to think differently about things. In other words, technological frames guide managers' interpretations of what a technology is and what it does.

2.3. Research into big data frames

We use *big data frames*, which are technological frames that refer to big data, including the assumptions, expectations, and beliefs that individuals possess and use to interpret and make sense of big data technologies. To date, only a few big data frames have been studied and described in the literature. Corbett and Webster (2015) identified and developed three big data frames they refer to as opportunity, control, and data limitation, which explain how an organization views big data and how these frames influence organizational actions. The opportunity frame expresses the innovation potentials individuals see in the data. The control frame reflects perceived control and influence over the data. The data limitation frame expresses the potential pitfalls or imperfections that individuals associate with big data. Corbett and Webster's (2015) single-case study is one of the first theoretically informed studies to examine technological frames in relation to big data.

Chan and Moses (2017) examined how agents in security production conceive big data as well as what capabilities and value big data will bring to their work. They propose two frames: the value frame, which describes the new opportunities and advantages big data affords relating to inferences from trends and patterns regarding security threats. This value frame has many similarities to the opportunity frame described by Corbett and Webster (2015). The second frame described by Chan and Moses (2017) manifests in concerns about privacy, misuse of data, data security and integrity, discrimination, political and reputational risks, and misplaced trust in a technology or algorithms. Highlighting anxieties regarding big data, the so-called risk frame is similar to Corbett and Webster's (2015) limitation frame, which expresses the potential pitfalls or imperfections of big data.

3. Methodology

We use Q-methodology to capture public managers' expectations, assumptions, and understandings about big data's uses in public administration. Q-methodology is particularly well suited for exploring subjective assumptions, expectations, values, and beliefs towards technology (Bouwman, Bejar, & Nikou, 2012; Klaus, Wingreen, & Blanton, 2010; Mettler, Sprenger, & Winter, 2017; Rahim, Lallmahomed, Ibrahim, & Rahman, 2011). According to (Stephenson, 1986), it is a constructive yet pragmatic methodology that differs in several ways to other research approaches. Compared to exclusively interpretive approaches, such as interpretive ethnography (Schultze, 2000) or case studies (Walsham, 1995, 2006), Q-methodology applies a quantitative interpretation technique, allowing for some generalizations about respondents' opinions similar to those obtained from positivist research, but without neglecting the fact that these results are socially constructed and based on respondents and researchers' subjectivity (Dziopa & Ahern, 2011). Differing from typical hypothesis-driven survey research, Q-methodology involves a so-called *concourse* as starting point of the research process, which seeks to collect a rich set of self-referential statements (i.e. opinions, not facts), each making a different yet nonetheless recognizable assertion about the topic under study (van Exel & de Graaf, 2005). Another distinguishing element is the fact that respondent selection is oriented to population diversity and not to a representative population sample. This may lead to unusual or counter-intuitive findings that are often not reported in typical survey-based studies (Zabala & Pascual, 2016). We will now describe the individual methodological phases and how we proceeded.

3.1. Concourse

A Q-methodology study typically starts with the collection of an initial statements set, known as the *concourse*, to capture a wide range of respondents' opinions, expectations, values, or beliefs. Akin to developing a battery of questions for a survey-based inquiry, this first step seeks to document stimulating statements, each with a different yet nonetheless recognizable assertion about big data in the public sector. Other than in hypothesis-driven research, the concourse must not necessarily be theory-driven or comprehensive; instead, it should reflect the phenomenon in a broad and engaging way (Watts & Stenner, 2012). Thus, according to Stephenson (1993, pp. 3–4), there is no correct or universal way to identify the ‘right’ number or content of a statement: more importantly, “[…] a distinction has to be drawn between matters of objective fact […] which are singular bits of information which do not spread, and matters of self-reference, which are infinite about anything.”

The initial concourse started with 32 semi-structured telephone interviews (in English or German) between April and June 2017. As proposed by Thompson (1966), we used a purposive sampling strategy and recruited our interview respondents either because they had a special interest in big data, for instance, political advisors (N = 2), consultants (N = 3), or promoters of big data solutions (N = 3) and/or because they were acknowledged as having special authority and expertise in big data, such as public IT managers (N = 8), researchers developing big data applications for the public sector (N = 3), and/or who could judge and provide dispassionate feedback about the implementation and use of big data in Switzerland, for instance public managers in financial control (N = 5). In this sampling process, we also considered the federal structures in Switzerland by actively involving politicians (N = 8) working in different governmental levels and agencies. With the interviewees' consent, we recorded and later transcribed all conversations. Each interview took approximately 60 min.' The guidelines for the collection of interview data contained five overarching topics: (a) the current use of big data (What is the status quo regarding the use of big data in Swiss public administration?), (b) the perceived benefits (What are the benefits of big data use for public administration?), (c) barriers (Which barriers hinder the implementation of big data in public administration?), and (d) areas of use (Which areas would benefit from use of big data, and how?), and (e) the requirements for the use of big data (What requirements are given or are needed for the use of big data?). These interviewees were not included in the Q-sorting step, which we will discuss in the next chapter.

3.2. Q-sample

The second step in Q-methodology, commonly known as the *Q-sample* or *Q-set* (Brown, 1993), seeks to select a manageable yet meaningful set of 20–100 statements, which serves as approximation of all opinions accumulated in the concourse (Valenta & Wigger, 1997; Watts & Stenner, 2012). Unlike instrument development in survey-based research, there are no clear rules or a predefined procedure on how to determine the number and wording of statements. To allow for diverse interpretations about the study subject, (Baker, Wildman, Mason, & Donaldson, 2014) suggested retaining the language used in previous conversations as much as possible, with the inherent duplication and looseness this implies for the Q-sample. On the other hand, (Akhtar-Danesh, Baumann, & Cordingley, 2008) proposed reducing ambiguity and removing certain statements to eliminate repetition that would confuse study participants and would prolong the later Q-sorting exercise. Based on the interview transcripts, we defined an initial set of 50 statements, which we then further reduced to 32 by merging similar and removing opposite statements, in order to target a response time of approximately 20 min per participant, given the oversaturation of survey requests in public administrations.

3.3. Q-sorting

The third step involves a card-sorting exercise, named *Q-sorting*, which is often considered to be the ‘core’ of Q-methodology. It is used to elicit a subjective perspective on a phenomenon by asking a respondent to position, iterate, and re-arrange the Q-sample statements on a continuum (ranging from *most agreeable* to *most disagreeable*) until they are comfortable with the cards' placement in relation to one another (Donner, 2004).

Based on list of known public managers, we used the snowballing technique (Myers & Newman, 2007) to recruit new respondents. We first made contact with them by telephone, informing them about the study goals; shortly thereafter, we sent them a personalized link to the software *Q-software* with specific instructions on how to do the sorting exercise online.

The entire procedure had two steps: first, the respondents randomly received one Q-sample statement at a time and were asked to drag-and-drop each card into one of three piles (i.e. agree, disagree, or neutral). After the respondents completed the initial sorting stage, we gave them the choice to review their piles and to make changes or continue. Second, we asked them to perform a rank-ordering (from 7 = items that were *most agreeable*, to 4 = *indifferent*, to 1 = *most disagreeable*). For reasons of simplicity and pragmatism (Baker et al., 2014; Valenta & Wigger, 1997), we asked them to put the statements they most agreed and most disagreed with in the designated box first; then the second-most agreed/disagreed with statements, and so on, until all slots were filled. In line with (van Exel & de Graaf, 2005), the chosen distribution's kurtosis (i.e. the allotment pattern's steepness) for distributing the cards

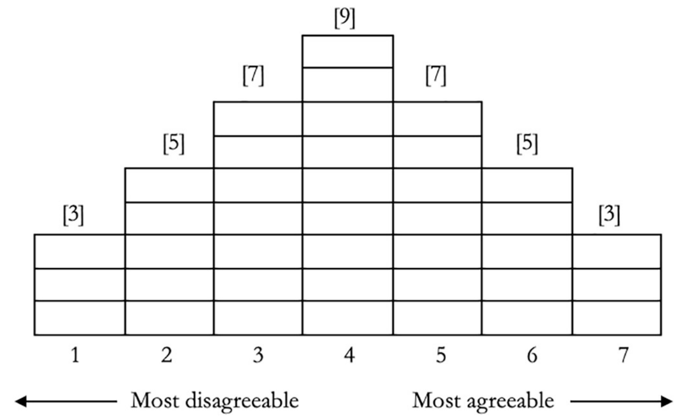

Fig. 1. Applied quasi-normal distribution for the Q-sorting of 39 statements.

(as shown in Fig. 1) followed a fairly flat predefined quasi-normal distribution, because we expected the respondents to have strong or well-articulated opinions about big data.

We received 64 responses from senior managers working in different governmental agencies in Swiss public administrations. The average response time for the Q-sorting was 17 min.

Although not specifically required in Q-methodology, our sample was highly representative and accurately reflects the distribution in the Swiss administration, with 87% male and 13% female senior managers (Schillingreport, 2017). The minimum age was 34 and the maximum 63 (average age: 52.8 years). The respondents were 86% male and 14% female. Around 42% rated their IT literacy as average, 39% as good, 15% as very good, and 3% as fair. Public managers from a wide range of departments in the Swiss administration participated (see Table A1 in the Appendix).

3.4. Quantitative data analysis as basis for qualitative interpretation

The last step in Q-methodology involves a quantitative factor analysis of the data in order to facilitate the qualitative interpretation of cognitive structures. (Watts & Stenner, 2012) recommended using principal component analysis (PCA) with Varimax rotation to pursue a rotated solution, which maximizes the amount of variance explained by extracted factors.

We used STATA software V14.2 to perform the recommended analysis, extracting a total of nine factors that accounted for 69% of the total variance. In line with (McKeown & Thomas, 1988), we opted for a nine-factor solution owing to theoretical and practical considerations instead of choosing factors purely based on the eigenvalue criterion (i.e. eigenvalue ≥ 1.00) as suggested by (Watts & Stenner, 2012). All retained factors were significant at the $p < .01$ level, complying with the guidelines defined by (Brown, 1993) and (McKeown & Thomas, 1988).[1] Factor loadings, normalized weighted average statement scores (*Z*-scores) as well as the statements most agreed and disagreed with per group, are shown in the Appendix.

4. Findings: big data frames in public administration

We will now provide an interpretation of the factors or frames we obtained from Q-methodology. First, notably, the frames we identified were neither unambiguous nor unique. As in real life, perceptions about a complex phenomenon are fairly ambivalent, multifaceted, and frequently intersecting in some respects (Harthorn, Shearer, & Rogers, 2011). In this sense, all nine frames shared some beliefs (see Table A3 in

[1] Significance at the $p < 0.01$ level is achieved when a factor loading is greater than 2.58 times the standard error for the loading (i.e. $SE = 1/\sqrt{N}$, where N is the number of statements) or, in our case, $2.58 \cdot (1\sqrt{32}) = 0.456$.

the Appendix, with consensus items), yet there are also major differences in the ways public managers perceive big data's value and roles in public administration (see Table A4 in the Appendix, with differentiating items). We will now briefly describe the main factors that characterize each of the nine technological frames.[2]

4.1. Group 1: outward-oriented techno-skeptics

Public managers in the first group are positioned at the outer ends of the two dimensions and have a decidedly negative stance towards big data use in public administration. We label this group *outward-oriented techno-skeptics*; it represents public managers with serious doubts about big data's benefits for both public administrations and society. A lack of trust and a skepticism about the introduction of big data technologies dominate this group. This group does not see big data as a major reason for change; it believes that its possibilities are limited and that the benefits are insufficient for initiating a major paradigm shift in public administrations. Although it emphasizes a broader perspective on big data's potentials and risks, this group sees no positive long-term effects for citizens and little transparency for a national economy. Above all, public managers in this group particularly resent the stronger state supervision and citizen surveillance that would presumably accompany the introduction of big data. Thus, they insist that citizens must always have ultimate control over their data. Table 1 shows the statements this group most agreed and disagreed with.

4.2. Group 2: inward-oriented techno-skeptics

The second group represents public managers who are critical about big data uses, primarily for reasons inherent to Switzerland's public administration's current structures and organization. We label this group *inward-oriented techno-skeptics*; its members show little enthusiasm for introducing big data in their organizations. The belief that big data encourages pseudo-accuracy in public decision-making is predominant in this group's worldview. Thus, it does not envision enough beneficial usage cases to justify public administration investing in big data. It also sees the application of big data in public administration as in its infancy. The two best-rated statements in this group illustrate two reasons for this attitude. First, it is convinced that big data is a buzzword that is poorly understood in public administrations. Public decision-makers who don't grasp big data's full potential hinder efficient use of big data in public administration. Second, this group's members share the view that a lack of technical know-how in analyzing growing data volume also hinders public administration's efficient use of big data. In its view, basic requirements such as big data standards must first be defined before any large-scale infrastructure is built. The statements inward-oriented techno-skeptics most agreed and disagreed with appear in Table 2.

4.3. Group 3: neutral observers

Compared to others, public managers in this group have a very balanced perspective on using big data in public administrations. Here, there is no denial of big data's relevance, but no glorification of it or of its benefits for both the general public and public administration either. For instance, this group strongly believes that big data helps to better anticipate the needs of, and improve service quality to, citizens, as well as supporting more effective and efficient use of resources in public administration. At the same time, it acknowledges that the current situation does not necessarily warrant a full introduction – there is no real need for public administrations to implement and use big data at this time, because traditional information sources are not yet fully exploited. We labeled this group *neutral observers*; it emphasizes big data's benefits for citizens (by taking the external perspective), but are reluctant about the internal perspective. Table 3 contains the statements this group most agreed and disagreed with.

[2] The sequence of how we present the nine groups of public managers followed the order of factor extraction shown in Table A1.

4.4. Group 4: general techno-enthusiasts

Members of this group see great opportunities in using big data, both for administrations and for the general public. This group strongly believes that big data use could help administrations to better anticipate and realize citizens' needs, also increasing government actions' transparency and effectiveness. It favors an experimental, trial-and-error approach to successfully master the introduction of and transition to efficient public administration usage of big data. While convinced that big data will improve public services' quality, it also shares the perception that big data poses a major threat to citizens' privacy. While such threats must be averted, it also sees a need for major improvements in data compatibility and comparability, the creation of new job profiles, and the institutionalization of a positive change culture in Swiss public administration. We call this group *general techno-enthusiasts*, since it strongly believes in big data's positive impacts and strongly believes that public administrations will be able to harness big data's full future potential. Table 4 contains the statements this group most agreed and disagreed with.

4.5. Group 5: inward-oriented techno-enthusiasts

Public managers in the group, labeled *inward-oriented techno-enthusiasts*, are positioned at the inner ends of the two dimensions and have a decidedly positive stance towards big data's use in public administrations. This group spots many affordances of big data and various opportunities to actively use it in their departments. Among others, big data is perceived to lead to better decision-making, more effective and efficient resource use, increased transparency, and better anticipation and realization of citizens' needs. This group is generally not skeptical of big data, but has concerns about public organizations' readiness and capabilities to master its introduction. The statements inward-oriented techno-enthusiasts most agreed and disagreed with appear in Table 5.

4.6. Group 6: inside observers

Members of this group are public managers who focus, first, on internal problems and take a balanced view of big data's use in public administrations. Although this group sees many benefits in big data, it doesn't believe that it will lead to a fundamental change in how public administrations will work in the future. Overall, it perceives the implementation of big data as problematic, because leadership and management in today's public administrations are unprepared for more data-driven or algorithmic governance. It also believes that a lack of technical know-how and standards regarding data compatibility and comparability, paired with Swiss federalism and uncertainties in legislation, hinder the successful introduction and use of big data in public administrations. We called this group *inside observers* owing to its strong internal orientation and balanced views on the risks and benefits of big data. Table 6 shows the statements this group most agreed and disagreed with.

4.7. Group 7: outward-oriented techno-enthusiasts

The next group of public managers is particularly outward-oriented, with a decidedly positive stance towards big data use in public administrations. We label this group *outward-oriented techno-enthusiasts*; it sees big data as a big opportunity to improve existing public services for citizens and businesses. Public managers in this group share the belief that big data increases public administrations' agility and creates

Table 1
Statements outward-oriented techno-skeptics most agreed and disagreed with.

No.	Q-statement	*Z*-score
30	Big data is a big source of danger to citizens' privacy.	7
25	Citizens must always have ultimate control over their data.	7
20	The application of big data in public administrations is still in its infancy.	7
14	Liberal legislation concerning data storage, analysis, and repurposing is needed if public administrations are to use big data efficiently.	1
8	Big data is a driver for improving public administration's image in society.	1
35	Public administrations should be allowed to sell collected data to third parties.	1

Table 2
Statements inward-oriented techno-skeptics most agreed and disagreed with.

No.	Q-statement	*Z*-score
13	Public decision-makers not perceiving big data's full potential hinders public administrations from using big data efficiently.	7
15	The lack of technical know-how in analyzing the growing volume of data hinders public administrations from using big data efficiently.	7
26	The lack of standards in public administrations regarding data compatibility and comparability hinders the effective use of big data.	7
22	Public administrations face internal resistance, because big data increases government actions' transparency.	1
35	Public administrations should be allowed to sell collected data to third parties.	1
37	The availability of real-time information increases public administrations' agility.	1

Table 3
Statements neutral observers most agreed and disagreed with.

No	Q-statement	*Z*-score
10	Leadership and management styles used in today's public administrations are not prepared for the use of big data.	7
19	Big data increases public administrations' service quality.	7
20	The application of big data in public administrations is still in its infancy.	7
9	Big data is just a governmental mass surveillance apparatus.	1
31	It is hard to find beneficial usage cases for big data in public administrations.	1
35	Public administrations should be allowed to sell collected data to third parties.	1

opportunities for entrepreneurs to establish new, innovative startups. To this group, it is easy to find many beneficial usage cases for big data in the public sector; only uncertainties in legislation and lack of standards are preventing public administrations from introducing big data. Thus, political support is needed to accelerate the slow adoption pace in Switzerland's public administration, so that major societal impacts can be realized. Table 7 shows the statements this group most agreed and disagreed with.

4.8. Group 8: outside observers

Public managers whom we called *outside observers* perceived both positive and negative effects for society from big data. This group believes that big data helps to better anticipate and realize citizens' needs and to identify governmental malpractice or misuse of resources. However, these positive effects are overshadowed by some skepticism; this group sees big data more as an additional source for further inequality in society. Instead of an opportunity for democratization, it sees big data as a big privacy risk for citizens, resulting in lower participation. From its perspective, big data will neither increase public policies' transparency nor enhance opportunities for entrepreneurs to establish new, innovative startups, because Swiss federalism, silo thinking in different departments, and uncertainties in legislation will impede major improvements, although minor improvements are conceivable. The statements outside observers most agreed and disagreed with appear in Table 8.

Table 5
Statements inward-oriented techno-enthusiasts most agreed and disagreed with.

No.	Q-statement	*Z*-score
1	Big data allows for more precise and efficient decision-making in public administrations.	7
4	Big data allows for more effective and efficient use of resources in public administrations.	7
25	Citizens must always have ultimate control over their data.	7
9	Big data is just a governmental mass surveillance apparatus.	1
17	There are no real needs in public administrations to implement and use big data.	1
35	Public administrations should be allowed to sell collected data to third parties.	1

4.9. Group 9: general techno-skeptics

The last group of public managers are *general techno-skeptics*. While this group perceives the status quo as inadequate, it does not feel that technological advancement will lead to major positive improvements in current public administrations. It has serious concerns that silo thinking in different departments and a general lack of technical know-how will impede the successful implementation of big data in the public sector. This group's negative attitude to the introduction and use of big data is particularly apparent when it assesses big data's impacts on society. For

Table 4
Statements general techno-enthusiasts most agreed and disagreed with.

No.	Q-statement	*Z*-score
25	Citizens must always have ultimate control over their data.	7
37	The availability of real-time information increases public administrations' agility.	7
2	Big data helps to better anticipate and realize citizens' needs.	7
15	The lack of technical know-how in analyzing the growing volume of data hinders public administrations from using big data efficiently.	1
29	The introduction of big data fuels power struggles in public administrations.	1
35	Public administrations should be allowed to sell collected data to third parties.	1

Table 6
Statements inside observers most agreed and disagreed with.

No.	Q-statement	Z-score
15	The lack of technical know-how in analyzing the growing volume of data hinders public administrations from using big data efficiently.	7
20	The application of big data in public administrations is still in its infancy.	7
34	Uncertainties in current legislation hinders public administrations from using big data efficiently.	7
18	Big data allows for greater participation of citizens in public decision-making.	1
22	Public administration faces internal resistance, because big data increases government actions' transparency.	1
35	Public administrations should be allowed to sell collected data to third parties.	1

Table 7
Statements outward-oriented techno-enthusiasts most agreed and disagreed with.

No.	Q-statement	Z-score
28	Big data in public administrations enhance the attractiveness for entrepreneurs to establish new, innovative startups.	7
37	The availability of real-time information increases public administrations' agility.	7
38	Support from politicians is needed to use big data effectively.	7
9	Big data is just a governmental mass surveillance apparatus.	1
24	Public administration is ready for big data, from a technical infrastructure perspective.	1
35	Public administrations should be allowed to sell collected data to third parties.	1

instance, it is convinced that big data does not lead to greater citizen participation in public decision-making; instead, it will encourage pseudo-accuracy and false arbitration of facts. Particularly in a direct democracy, as is the case in Switzerland, this could have massive impacts on voting decisions and government's resource allocation. Table 9 shows the statements this group most agreed and disagreed with.

5. Discussion and conclusion

We began by stating that the de facto uses of big data in public administration are very limited, because government organizations are postponing decisions on big data use, because they are unsure whether or not to implement big data, and how (Klievink et al., 2017). We then reviewed the literature on the upsides and downsides of big data in public administrations and highlighted promising effects for government and society (Chen et al., 2012) or outlined risks and challenges from big data usage. There are many reasons for and against the use of big data in public administration. This dilemma could to some extent explain the existing uncertainties and explain why government organizations are postponing decisions on big data use. We suspected that government organizations' uncertainty about whether and how to implement big data arises from public managers' very different opinions, expectations, assumptions, and understandings of big data usage in public administration. To date, their perceptions and understandings of big data have remained unobserved – there was no attention to whether public managers perceive big data as an opportunity or risk, or to what affordances they associate with this technology. To close this gap, we used technological frames analysis (Orlikowski & Gash, 1994) to uncover public managers' technological frames concerning big data, including the assumptions, expectations, and beliefs they possess and use to interpret big data.

5.1. Contributions

Our results showed there are diverse ideas in public administration about what big data is and what it does. While some public managers have a clear positive or negative perception of big data, others form more complex, nuanced cognitive structures. Although the literature has not specifically concentrated on the systematic study of public managers' perspectives, our study reflects previous research's findings on perceived technological opportunities (Klievink et al., 2017; Lavertu, 2016) and threats of big data usage in the public sector (Chen et al., 2012). However, unlike these studies, which explored big data as an aggregate socio-technical phenomenon (which typically suppresses public managers' key roles in influencing civil servants' behaviors and mindsets or in actively shaping a political agenda in favor or against the introduction of big data), we have focused on understanding the perceptions and views of those who manage and decide whether or not to implement big data in public administration, and how. Each of the nine big data frames we identified describes a different position on the use of big data in public administrations. Different big data frames imply different interpretations and understandings of technology. As evidenced by Orlikowski and Gash (1994), such incongruences in technological frames can hinder the implementations and uses of technology.

Despite the differences between big data frames, there are also shared thought patterns across the groups, making it difficult to clearly classify potential advocates and inhibitors of big data. Our interpretation of the Q-samples has led us to conclude that public managers share distinct levels of techno-enthusiasm or skepticism towards big data. Here, our results correspond to those on big data in the literature, i.e. the opportunity/value frames and the risks/limitations frame (Chan & Moses, 2017; Corbett & Webster, 2015), and reflects the expectations of and anxieties about big data in public administrations. However, the nine frames we identified show much more differentiated opinions, expectations, assumptions, and understandings in public administration. We have also seen that an inward or outward orientation (i.e. the extent to which a public manager focuses on internal or societal effects) plays a key role in public managers' perceptions of affordances or constraints. These two aspects are strongly interwoven and thus need to be considered simultaneously if one is to understand a public manager's perspective on big data. We may say that the more (less) importance and positive (negative) valence public managers attach to big data, the

Table 8
Statements outside observers most agreed and disagreed with.

No.	Q-statement	Z-score
6	Silo thinking in different departments hinders public administrations from using big data efficiently.	7
7	Federalism hinders public administration from using big data efficiently.	7
10	Leadership and management styles used in today's public administrations are unprepared for the use of big data.	7
5	The use of big data in public administrations will increase government actions' transparency.	1
35	Public administrations should be allowed to sell collected data to third parties.	1
39	Big data represents an opportunity for democratization.	1

Table 9
Statements general techno-skeptics most agreed and disagreed with.

No.	Q-statement	Z-score
7	Federalism hinders public administration from using big data efficiently.	7
25	Citizens must always have ultimate control over their data.	7
26	The lack of standards in public administrations regarding data compatibility and comparability hinders the effective use of big data.	7
9	Big data is just a governmental mass surveillance apparatus.	1
22	Public administration faces internal resistance, because big data increases government actions' transparency.	1
35	Public administrations should be allowed to sell collected data to third parties.	1

higher (lower) effort will be devoted to promoting and implementing big data in public administrations. The widespread skepticism and uncertainties among the nine big data frameworks we identified help us to understand why the de facto usages of big data in the public sector remain very limited.

Notably, all identified big data frames, ranging from inward-oriented techno-enthusiasts to outward-oriented techno-skeptics, occurred regardless of public managers' backgrounds, i.e. the department they manage, their age, gender, or IT literacy (see Table A1). Thus, our results are not limited to managers with an affinity to digitalization such as Chief Information Officers, but also include the perceptions and understanding of public managers in education, justice, construction, environment, military, finance, culture, or security. Accordingly, all nine big data frames we identified are spread across all departments, age groups, or administrative professions. Knowing and understanding these technological frames in public administration is critical for broad and seamless technology implementation, including but not limited to big data. Having knowledge of potential promoters or inhibitors as well as their value projections regarding a specific technology represents a key tactical advantage before, during, and after the implementation of this technology. We will now discuss these practical implications in some detail.

5.2. Implications for practice

Similarly to Mergel et al. (2018), our approach highlighted the added value of unlocking the perceptions of public managers, since they provide important insights into how those responsible for implementing and generating via big data actually interpret and understand big data. The implementation of big data in public administrations is not necessarily a question of technological feasibility, but of acceptance and will. Thus, we should focus not only to the technical dimension, but especially on the social dimension.

For practice, our study holds implications for big data implementation in public administration. First, our findings showed that there is no single view, but diverging opinions. Each technological frame represents a commonly held view. We have also highlighted inconsistencies between different perceptions among public managers. If not articulated or discussed, they can result, unintentionally and unknowingly, in misaligned expectations or contradictory actions (Orlikowski & Gash, 1994). Inconsistencies in big data frames are likely to lead to problems in implementation. They pose challenges for defining organizational and technical standards and make it hard to agree on a shared vision, strategy, or future roadmap. Our results can help policymakers to identify the ways in which big data are perceived by various groups of public managers, allowing the identification of common issues or opinions. Understanding the different big data frames in public administration may also help policymakers to develop common standards and strategies. Public policies that address widely shared concerns among public managers are likely to gain broad acceptance, legitimacy, and support, and are therefore more likely to be effective. Thus, policymakers can ensure that maximum value can be derived from big data technology in public administration.

Second, we have highlighted potential responses to big data use in public administration. Our findings revealed widespread skepticism among public managers. If not addressed, skepticism can result in unanticipated organizational consequences, such as resistance, and spotty acceptance (Orlikowski & Gash, 1994). Understanding public managers' reservations about the use of big data in public administration and uncovering any cognitive misperceptions and misunderstandings may help to address these concerns from the outset. This may prevent massive group disappointments, may counteract resistance, and thus may facilitate the adoption and implementations of big data in public administration.

5.3. Limitations and future work

We conclude by pointing out three main limitations and corresponding implications for future research. First, as mentioned at the start, we investigated big data frames in an initial implementing stage of big data in public administration. Since the implementation of big data in Switzerland's public administration was still in its infancy at the time of this study, we cannot draw any conclusions about how these frames will affect the implementation and uses of big data; this needs to be clarified by future research. Future research may also examine how frames change once big data is implemented in public administrations.

Second, starting with the premise that studying subjectivity is a worthwhile research goal, we used Q-methodology to explore, describe, and interpret big data frames. This gives researchers some room to maneuver (e.g. number and distribution of Q-sorts, qualitative interpretation of factor scores). It also does not detail the structure or causality leading to a big data frame, nor how they are interrelated. Q-methodology's results are always bound to a specific context and time. Thus, our findings are by no means representative; instead, they represent the current understandings among public managers in Switzerland's public administration. It is possible that significantly different big data frames exist in other parts of the world, or that the identified big data frames will change or not endure over time. Additional research is needed to better understand how big data frames evolve and change depending on a study context.

Third, in democratic states, perceptions, opinions, and understandings of society are a key influencing factor regarding the acceptance and successful implementation of big data in public administrations. Thus, it is important for future studies to investigate big data frames outside public administrations. It would be interesting to see how big data frames inside and outside public administration coincide and differ. Research that considers this could contribute to an overall better understanding of big data's social dimension and could bring about richer theoretical and practical insights.

Fourth, although the different technological frames we identified and discussed contribute to a deeper understanding of the different perceptions of public managers, our results remain descriptive and do not allow causal inferences. Further studies are needed to understand and explain why and how such diversity and distribution occur. We also call on researchers to analyze factors that influence managers' views and perceptions of big data.

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Appendix

Table A1
Study participants (N = 64) ordered by factor loadings.

Public agency or department	Age	Gender	Literacy	G_1	G_2	G_3	G_4	G_5	G_6	G_7	G_8	G_9
Department for Culture	60	Female	Average	**0.830**[a]	0.233	−0.193	−0.003	0.024	0.222	−0.016	−0.038	0.08
Department of Finance	50	Female	Very good	**0.770**[a]	0.014	0.061	−0.073	0.118	−0.005	−0.044	0.056	0.198
Department of Agriculture and Forestry	62	Male	Average	**0.714**[a]	0.348	−0.363	0.197	−0.068	0.114	−0.033	0.061	−0.036
Department of Economic Affairs	49	Male	Average	**0.712**[a]	0.274	0.182	0.077	−0.021	0.22	0.106	0.008	−0.022
Department of Buildings	52	Male	Average	**0.702**[a]	0.044	0.105	−0.087	0.07	0.007	0.021	0.177	0.16
Department for Colleges and Universities	60	Male	Average	**0.701**[a]	0.109	0.073	0.322	0.04	0.317	−0.221	−0.058	−0.261
Department of Finance	48	Male	Good	**0.575**[a]	0.235	0.475	0.066	0.048	0.049	0.046	0.277	0.321
Department of Military and Civil Defense	50	Male	Average	**0.575**[a]	−0.039	−0.115	0.089	0.345	0.122	−0.202	0.394[a]	0.198
Forestry Department	60	Male	Average	**0.569**[a]	0.191	0.414	0.127	0.171	0.254	0.156	0.046	−0.285
Department of Buildings	60	Female	Good	**0.558**[a]	0.131	−0.025	0.28	0.294	0.315	−0.193	0.025	−0.049
Department for Culture	50	Male	Good	**0.547**[a]	0.162	0.275	0.071	0.244	0.141	0.326	0.269	0.298
Department of Finance	47	Male	Good	**0.492**[a]	0.118	0.12	0.480[a]	0.143	−0.09	0.241	0.271	−0.298
Department of Justice and Home Affairs	56	Female	Poor	**0.471**[a]	−0.41	0.029	0.315	0.288	0.323	−0.079	0.171	0.129
Department of Vocational Training	34	Male	Average	**0.445**	0.436	−0.008	0.37	0.074	0.342	−0.046	−0.034	−0.124
Department of Health	52	Male	Very good	0.067	**0.742**[a]	−0.246	−0.141	0.091	0.213	0.173	0.212	0.124
Department of Informatics	51	Male	Very good	0.244	**0.742**[a]	0.04	0.027	−0.143	0.078	−0.165	0.103	0.17
Department of Economy and Labor	41	Female	Good	0.13	**0.718**[a]	0.101	0.082	0.175	0.143	−0.021	−0.02	−0.152
Department of Health and Social Affairs	54	Male	Good	0.04	**0.699**[a]	−0.078	0.098	0.135	0.09	0.147	0.004	0.424
Department of Education, Culture and Sport	40	Female	Average	0.403	**0.690**[a]	0.284	0.049	−0.136	0.084	−0.104	−0.004	0.039
Department of Buildings	47	Male	Very good	0.059	**0.686**[a]	−0.12	−0.213	−0.076	0.081	0.047	0.095	0.207
Department for Colleges and Universities	62	Male	Average	0.072	**0.590**[a]	0.225	0.142	0.444	0.186	−0.174	0.163	−0.228
Department of Informatics	52	Male	Good	0.192	**0.418**	0.402[a]	−0.128	−0.287	0.348	0.332	0.105	0.036
Department of Education and Culture	58	Male	Good	−0.208	−0.027	**0.797**[a]	0.095	0.18	−0.004	0.005	0.249	0.112
Department of Finance	63	Male	Average	−0.079	−0.154	**0.714**[a]	0.03	0.169	0.044	0.079	0.048	−0.098
Department of Justice, Police and Military	57	Male	Good	0.253	0.149	**0.523**[a]	−0.104	0.286	0.199	0.026	−0.016	0.062
Department of Health	53	Male	Good	0.405	0.124	**0.517**[a]	0.085	−0.088	0.092	0.164	−0.215	0.026
E-Government Department	50	Male	Very good	0.32	0.037	**0.506**[a]	0.319	0.231	0.209	0.355	−0.101	0.206
Department of Education	52	Male	Average	0.32	−0.084	**0.463**[a]	0.41	0.117	−0.154	0.24	0.365	−0.095
Department of Education	48	Male	Good	0.241	0.252	**0.453**	0.236	0.32	0.168	0.337	−0.157	−0.009
Department of Health and Welfare	45	Female	Average	0.064	0.123	−0.074	**0.812**[a]	0.102	0.106	0.155	−0.019	0.008
Department of Health	51	Male	Good	−0.016	−0.119	0.006	**0.667**[a]	0.222	0.261	0.069	0.035	−0.116
Department of Security	52	Male	Good	−0.03	0.036	0.486[a]	**0.660**[a]	0.23	0.249	0.051	−0.24	0.003
Department of Finance	56	Male	Very good	0.284	0.146	0.047	**0.576**[a]	−0.048	0.13	−0.155	0.322	0.35
Department of Construction and Transport	46	Male	Good	0.218	−0.165	0.154	**0.564**[a]	0.188	−0.218	0.492	0.151	−0.054
Department of Justice, Security and Health	61	Male	Good	0.256	0.267	0.391	**0.557**[a]	0.17	−0.005	−0.157	−0.302	0.208
Department of Construction and Environment	54	Male	Good	0.242	−0.236	−0.219	**0.516**[a]	0.113	−0.046	−0.37	0.199	0.098
Presidential Department	57	Female	Average	−0.045	−0.155	0.143	**0.505**[a]	−0.006	0.303	0.094	0.316	0.148
Department of Economic Affairs	59	Male	Good	−0.179	−0.126	0.371	**0.485**[a]	0.444	−0.033	0.322	0.148	0.135
Department of Buildings	63	Male	Very good	0.142	0.055	0.183	0.154	**0.684**[a]	−0.048	0.143	0.198	0.196
Department of Construction and Environment	54	Male	Average	0.276	−0.126	−0.008	0.041	**0.662**[a]	0.021	0.324	0.035	0.038
Department of Education	53	Male	Good	−0.222	−0.035	0.19	0.243	**0.572**[a]	0.382	0.053	0.203	0.02
Department of Education and Culture	37	Male	Very good	0.37	0.054	0.173	0.165	**0.554**[a]	0.066	0.337	0.076	0.006
Department of Finance	42	Male	Average	−0.243	−0.189	0.342	0.244	**0.547**[a]	0.171	0.19	0.002	0.414
Department of Finance	52	Male	Good	0.063	0.058	0.475[a]	0.021	**0.530**[a]	−0.195	−0.065	0.362	0.125
Department of Education and Culture	62	Male	Average	0.102	0.102	0.213	0.363	**0.516**[a]	0.314	−0.005	−0.116	0.276
Department of Construction and Environment	56	Male	Very good	0.237	0.32	0.06	0.155	**0.497**[a]	0.221	0.057	0.023	−0.147
Department of Education, Culture and Sport	60	Male	Average	0.013	−0.047	0.251	0.252	**0.475**[a]	0.269	0.400[a]	0.031	−0.065
Department of Justice and Security	57	Male	Good	0.245	−0.011	0.108	0.168	0.156	**0.773**[a]	0.085	−0.051	0.057
Department of the Environment	60	Female	Good	0.132	0.191	0.265	0.207	0.232	**0.659**[a]	0.123	−0.085	0.299
Department of Economics and Home Affairs	54	Male	Good	0.221	0.406	−0.021	0.03	−0.039	**0.645**[a]	−0.053	−0.123	0.069
Department of Economics and Home Affairs	59	Male	Average	0.195	0.181	−0.083	0.204	−0.114	**0.626**[a]	−0.122	0.032	−0.146
Department of Finance	44	Male	Average	0.162	0.253	0.053	0.01	0.162	**0.614**[a]	0.118	0.271	0.049
Department of Home Affairs and Security	35	Male	Average	0.241	0.257	0.291	−0.065	0.212	**0.497**[a]	−0.062	0.324	0.054
Department of Buildings	56	Male	Average	0.087	0.036	0.019	0.099	0.159	−0.135	**0.816**[a]	0.094	0.131
Department of Education and Culture	54	Male	Very good	−0.061	−0.089	0.402	0.169	0.057	0.404	**0.670**[a]	0.019	0.028
Department of Finance	43	Male	Good	−0.317	−0.017	0.009	−0.061	0.245	−0.029	**0.633**[a]	0.008	0.05
Department of Economic Affairs	59	Male	Average	−0.22	0.242	−0.106	0.328	0.216	0.342	**0.449**	0.134	0.088
Department of Finance	52	Male	Average	0.263	0.083	−0.134	0.048	0.297	0.165	0.044	**0.772**[a]	0.062
Department of Finance	55	Male	Good	−0.003	0.214	0.128	0.155	0.038	−0.104	0.073	**0.731**[a]	−0.007
Department of Economic Affairs	57	Male	Poor	0.35	0.33	0.23	−0.049	0.155	0.27	0.308	**0.480**[a]	−0.009
Department of Education	56	Male	Good	0.307	−0.047	0.378	−0.087	−0.024	0.278	0.443	**0.466**[a]	0.281
Department of Economics and Home Affairs	50	Male	Average	0.135	0.18	−0.026	0.075	0.193	0.093	0.026	−0.01	**0.759**[a]
Department of Economic Affairs	55	Male	Average	0.117	0.42	0.104	0.048	−0.086	0.041	0.225	0.188	**0.535**[a]
Department of Police and Military Affairs	57	Male	Average	0.184	0.074	0.285	−0.175	0.391	−0.116	0.319	0.127	**0.461**[a]
	Eigenvalues:			16.184	7.303	4.574	3.822	3.134	2.494	2.413	2.232	2.053
	Percentage of variance explained			25.28%	11.41%	7.15%	5.97%	4.89%	3.89%	3.77%	3.49%	3.21%

[a] Factor loadings that were significant.

Table A2
Mean and standard deviations of Q-statements over the entire sample and user groups' *Z*-scores.

No.	Q-statement	M	SD	G_1	G_2	G_3	G_4	G_5	G_6	G_7	G_8	G_9
1	Big data allows for more precise and efficient decision-making in public administrations.	4.672	1.448	3	3	6	5	7	5	5	5	3
2	Big data helps to better anticipate and realize citizens' needs.	4.984	1.266	4	4	6	7	6	4	6	6	4
3	Big data enables public administrations to improve their administrative processes, ultimately improving relationships with the private sector.	3.688	1.320	3	2	5	4	4	3	3	3	2
4	Big data allows for more effective and efficient use of resources in public administrations.	4.516	1.584	3	2	6	5	7	6	4	5	6
5	The use of big data in public administrations will increase government actions' transparency.	4.000	1.543	3	3	5	6	5	5	4	1	4
6	Silo thinking in different departments hinders public administration from using big data efficiently.	4.000	1.968	4	3	4	2	4	2	4	7	6
7	Federalism hinders public administrations from using big data efficiently.	4.453	1.781	5	4	3	3	5	5	4	7	7
8	Big data is a driver for improving public administration's image in society.	3.016	1.496	1	3	2	2	3	3	4	2	5
9	Big data is just a governmental mass surveillance apparatus.	3.016	1.667	5	2	1	4	1	3	1	4	1
10	Leadership and management styles used in today's public administrations are unprepared for big data' use.	4.828	1.559	6	6	7	3	5	6	3	7	4
11	Big data encourages pseudo-accuracy and elaborateness of public decision-making.	4.063	1.592	6	5	2	4	2	4	2	4	6
12	Public-private-partnerships are needed for the successful introduction of big data in public administrations.	3.266	1.693	2	4	3	4	3	2	4	4	3
13	Public decision-makers not perceiving the full potential of big data hinders public administration from using big data efficiently.	4.438	1.457	4	7	5	2	6	4	3	3	6
14	Liberal legislation concerning data storing, analysis, and repurposing is needed so that public administrations can use big data efficiently.	3.359	1.776	1	5	3	3	3	6	5	5	4
15	The lack of technical know-how in analyzing the growing volume of data hinders public administrations from using big data efficiently.	4.703	1.649	6	7	4	1	6	7	6	5	3
16	Big data is simply a buzzword nobody really understands in public administrations.	3.688	1.521	5	6	3	2	2	3	3	2	4
17	There is no real need in public administrations to implement and use big data.	3.922	1.646	5	6	6	3	1	4	2	3	4
18	Big data allows for a greater participation of citizens in public decision-making.	3.438	1.379	2	3	4	4	4	1	4	3	2
19	Big data increases public administrations' service quality.	4.672	1.310	4	3	7	6	5	5	6	4	4
20	The application of big data in public administrations is still in its infancy.	5.594	1.165	7	6	7	5	6	7	6	5	5
21	Big data helps public administrations to identify governmental malpractices.	4.156	1.586	5	4	5	4	5	4	5	5	2
22	Public administrations face internal resistance, because big data increases government actions' transparency.	2.781	1.464	2	1	4	2	2	1	5	2	1
23	With the introduction of big data, there is also the need to create new occupational profiles in public administrations.	4.609	1.508	6	5	5	5	6	4	5	6	2
24	Public administrations are ready for big data from a technical infrastructure perspective.	3.297	1.164	3	4	4	4	3	3	1	3	2
25	Citizens must always have ultimate control over their data.	5.547	1.479	7	5	5	7	7	4	4	5	7
26	The lack of standards in public administrations regarding data compatibility and comparability hinders the effective use of big data.	4.844	1.394	5	7	6	6	4	6	5	4	7
27	A positive culture of change is required in a public administration if it is to successfully introduce big data.	4.484	1.272	5	4	5	5	4	4	5	3	6
28	Big data in public administrations enhances the attractiveness for entrepreneurs to establish new, innovative startups.	3.688	1.332	3	4	3	4	3	2	7	2	5
29	The introduction of big data fuels power struggles in a public administration.	2.781	1.091	2	2	3	1	2	2	4	2	3
30	Big data is a great source of danger to citizens' privacy.	4.453	1.642	7	4	2	6	4	5	3	6	3
31	It is not easy to find beneficial usage cases for big data in public administrations.	3.297	1.388	4	6	1	3	2	3	2	4	4
32	Public administrations need to first enhance data management practices and quality of existing sources before thinking of harnessing data from sensors and smart devices.	4.203	1.416	6	5	3	5	5	6	2	4	5
33	Viability and profitability are not central for big data, since its main purpose is to improve existing and to create new public services that are valuable to citizens.	3.641	1.557	4	2	2	4	3	5	2	3	5
34	Uncertainties in current legislation hinders public administrations from using big data efficiently.	4.609	1.317	4	4	4	5	3	7	6	6	5
35	Public administrations should be allowed to sell collected data to third parties.	1.578	0.989	1	1	1	1	1	1	1	1	1
36	An experimental, trial-and-error approach is required to successfully introduce and transition to the efficient use of big data.	4.031	1.181	3	5	4	6	5	3	3	4	4
37	The availability of real-time information increases public administrations' agility.	4.297	1.610	4	1	4	7	4	4	7	4	3
38	Support from politicians is needed to use big data effectively.	4.234	1.354	4	5	4	3	4	5	7	6	5
39	Big data represents an opportunity for democratization.	3.156	1.263	2	3	2	3	4	2	3	1	3

Table A3
Consensus items (top five based on variance of *Z*-score).

No.	Q-statement	G_1	G_2	G_3	G_4	G_5	G_6	G_7	G_8	G_9	SD
35	Public administrations should be allowed to sell collected data to third parties.	1	1	1	1	1	1	1	1	1	0.000
12	A public-private-partnership is needed for the successful introduction of big data in a public administration.	2	4	3	4	3	2	4	4	3	0.694
20	The application of big data in public administrations is still in its infancy.	7	6	7	5	6	7	6	5	5	0.750
29	The introduction of big data fuels power struggles in a public administration.	2	2	3	1	2	2	4	2	3	0.750
39	Big data represents an opportunity for democratization.	2	3	2	3	4	2	3	1	3	0.778

Table A4
Differentiating items (top five based on variance of Z-score).

No.	Q-statement	G_1	G_2	G_3	G_4	G_5	G_6	G_7	G_8	G_9	SD
13	Public decision-makers not perceiving big data's full potential hinders public administrations from using big data efficiently.	4	7	5	2	6	4	3	3	6	2.778
30	Big data is a great source of danger for citizens' privacy.	7	4	2	6	4	5	3	6	3	2.778
17	There is no real need in public administrations to implement and use big data.	5	6	6	3	1	4	2	3	4	2.944
37	The availability of real-time information increases public administrations' agility.	4	1	4	7	4	4	7	4	3	3.444
15	The lack of technical know-how in analyzing the growing volume of data hinders public administrations from using big data efficiently.	6	7	4	1	6	7	6	5	3	4.000

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Ali A. Guenduez Ali A. Guenduez is Assistant Professor of Digital Government and Head of Smart Government Lab at the University of St.Gallen. His research interests include technology adoption, digital transformation, public sector innovation and smart government.

Tobias Mettler Tobias Mettler is Associate Professor at the Swiss Graduate School of Public Administration, University of Lausanne. His research interests are in the area of design science research, technology adoption, applications of data science, and business models, with a particular focus on public sector innovation.

Kuno Schedler Kuno Schedler is Full Professor at the University of St.Gallen. His main research topics are accounting and controlling in the public sector, general management in public administration, public governance and corporate governance, multirational management, electronic government and smart government.