Assessing e-Government maturity using country-level data: a fsQCA analysis

McManus, R.

Assessing e-Government maturity using country-level data: a fsQCA analysis

McManus, R.

Assessing e-Government maturity using country-level data: a fsQCA analysis

Completed Research

Federico Iannacci
University of Sussex
Falmer, United Kingdom
f.iannacci@sussex.ac.uk

Richard McManus
Canterbury Christ Church University
Canterbury, United Kingdom
richard.mcmanus@canterbury.ac.uk

Christian Rupietta
University of Wuppertal
Wuppertal, Germany
rupietta@uni-wuppertal.de

Gianluigi Viscusi
Imperial College London
United Kingdom
g.viscusi@imperial.ac.uk

Stan Karanasios
University of Queensland
Brisbane, Australia
s.karanasios@uq.edu.au

Abstract

Drawing on panel data, we undertake a fuzzy-set Qualitative Comparative Analysis (fsQCA) of the determinants of high levels of the e-Government Development Index (EGDI) in the period ranging from 2003 to 2020. Our analysis showcases multiple pathways to the outcome of interest, thus bypassing partially-conflicting findings regarding the role that human capital plays as a contributor to high EGDI. Furthermore, our analysis leverages the idea of equifinality by showing two models of change working in parallel, namely incremental models of change (typical of developed countries) and punctuated equilibrium models (typical of developing and middle-income countries). This, in turn, shifts the focus of configurational thinking from theorizing a limited number of stable patterns towards utilizing configurations as ways of understanding evolutionary trajectories of change and development. Implications for theory and practice are discussed by shedding a new light on e-Government maturity thanks to the use of fsQCA techniques in a deductive fashion.

Keywords: Change Models; Configurational Theorizing; e-Government Maturity; fsQCA

Introduction

E-Government maturity is a broadly used term to refer to the process by which public sector organizations progress through different stages of e-Government evolution (Klievinik and Janssen, 2009). Although there is no agreed upon metric to define e-Government maturity (e.g., Krishnan et al., 2017 used the Online Service Index, whereas Das et al., 2017 used West's and his associates' 2002-2008 criteria to focus on "the number of services delivered online"), one could argue that the use of longitudinal panel data is a necessary requirement to measure e-Government maturity because the concept of e-Government maturity is inextricably related to process theories of change (Poeppelbuss et al., 2011). Considering that researchers across various fields have associated higher maturity levels with better performance (Cf. Bititci et al., 2015: 3063; Lasrado et al., 2015: 8), in this paper, we turn to the literature on e-Government success (Scott et al., 2016) to define e-Government maturity. In other words, we conceive of e-Government maturity as both the process and the outcome of the successful enactment of e-Government. As countries enact more efficient and effective e-Government, they become more successful in their provision of online services. Hence, in line with extant IS success research (DeLone and McLean, 1992; 2003), we regard e-Government maturity as a complex construct that encompasses both temporal and causal dimensions. Put differently, our underlying assumption is that e-Government maturity combines the perspectives of *technological change* (i.e., various technologies featuring their own evolutionary trajectories) and *teleology* (i.e., the purposeful adoption of such technologies in an "adaptive and scalable manner" (UN, 2014: 34). While early definitions of e-Government maturity pointed to an incremental process of change (Lasrado et al., 2015, Poeppelbuss et al., 2011), more recent theorizations point to punctuated equilibrium models of change where e-Government trajectories are punctuated by radical shifts or changes (Pittaway & Montazemi, 2020). Studying the trajectories of e-Government development is important both for academics and policy makers because it enables policy makers to plan the way forward toward a desired end goal while helping academics to tackle hitherto unresolved dilemmas.

Despite the vast amount of research on e-Government maturity (Andersen and Herinksen, 2006; Layne and Lee, 2001; Lee, 2010; etc.), extant research seems to point to different and, at times, contradictory findings about its key conditions. For example, Das et al. (2017: 422) suggest "that Gross Domestic Product (GDP) and Information & Communication Infrastructure (ICT) may be sufficient conditions for e-Government maturity, as measured by West and associates. In other words, it might be possible for a country, willing and able to make investments in technological capabilities, to advance its e-Government maturity without necessarily rebuilding public sector processes." Indeed, they go on to argue that e-Government can develop, indeed flourish, without significant dependence on other factors such as human capital (an educated citizenry) and good governance (transparency, accountability, and effectiveness). Other scholars instead suggest that "the investment in human capital generates returns in future [sic] Therefore, investments in human capital will ensure the growth and maturity of e-Government systems and enhancement of Government's willingness to implement e-Participation for promoting citizen engagement" (Krishnan et al., 2017: 308). Moreover, the fact that human capital can be a contributing factor to e-Government maturity for one stream of literature (e.g., Krishnan et al., 2017) while being an irrelevant factor for another stream of literature (e.g., Das et al., 2017) raises the issue of validity. Are these findings truly inconsistent? Or can they be reconciled somehow? In this paper, we argue that one way to move beyond these partially-conflicting findings is to remove the linear assumptions that inform current research on e-Government maturity (e.g., Das et al., 2017: 424) and take a more systemic approach to the study of e-Government maturity drawing upon new methodological developments available in the e-Government scholars' toolkit (Dawson et al., 2016; El Sawy et al., 2010; Park et al., 2021). Following the argument that e-Government maturity is inextricably related to process theories of change (Poeppelbuss et al., 2011), we use longitudinal panel data as a necessary requirement to study e-Government maturity. More specifically, by using fuzzy-set Qualitative Comparative Analysis (fsQCA) on panel data ranging from 2003 to 2020 (UN, 2003, 2004, 2005, 2008, 2010, 2012, 2014, 2016, 2018, 2020), we aim to show that, far from working in isolation, each contributing factor works in combination with other factors so much so that there can be multiple configurations leading to the envisioned end goal (i.e., keeping up with technological development). This argument, in turn, switches e-Government scholars' focus from the assessment of the "net effects" of analytically-separate variables to a more contextual understanding of the multiple possible ways causal conditions combine to produce a given effect.

Drawing on the aforementioned e-Government success research stream on the quest for the dependent variable (DeLone and McLean, 1992; Scott et al., 2016), in this paper, we ask the following research questions:

1) *What conditions lead countries to high levels of e-Government performance over time?*

2) *In what way do these conditions combine to achieve high levels of e-Government performance over time?*

By addressing these questions, our study makes a significant contribution to extant e-Government maturity research in three distinct ways.

First, we conceptualize e-Government maturity as a complex, multifaceted construct encompassing both temporal (i.e., longitudinal aspects) and causal dimensions that conjointly affect the outcome of interest (i.e., e-Government performance). Drawing on the neo-configurational perspective (Misangy et al., 2017), our study proposes a novel way of thinking about causality where causes work in conjunction with each other rather than separately to produce the outcome of interest. Far from assuming uniformity, i.e., the same conditions/variables are involved in each instance of the outcome, and additivity, i.e., conditions/variables have the same effect on the outcome regardless of the value of other conditions/variables, our study shows that there are multiple configurations (or combinations) of causal conditions leading to the outcome of interest.

Second, our contribution leverages the idea of equifinality (i.e., multiple paths leading to high EGDI) by showing two models of change working in parallel, namely incremental models of change (typical of developed countries) and punctuated equilibrium models (typical of developing and middle-income countries). Though most developed countries feature regular trajectories of e-Government evolution, it turns out that developing and middle-income countries hook themselves up into technological trajectories only to be disrupted by sudden and unexpected turning points (Abbott, 2001). While developed countries have the resources to stay on course with technological development (Das et al., 2017), the goal of policy makers in developing and middle-income countries is to set themselves up into steady trajectories to keep up with the pace of technological change. However, internal and external shocks may cause tensions so much so that developing and middle-income countries may move into new paths or trajectories that display a slower pace (or rate) of technological development. Put differently, it often happens that, despite policy makers ambition to keep up with the pace of technological change, "outdated policies, budgetary constraints, inadequate technical skills and lack of leadership" (UN, 2012: 96) may cause tensions that move developing and middle-income countries into a slower pace of technological development. While turning points may redirect trajectories towards a slower pace of technological development, it may also happen, at times, that sudden changes may switch the trajectory of e-Government evolution towards a faster pace of development.

Third, and last, we use fsQCA analysis with panel data (Nishant and Ravishankar, 2020) to showcase the use of a novel technique with longitudinal data and highlight "common transitions, evolutionary trajectories, and movements between stages of a life cycle" (Miller, 2018: 462). Though e-Government scholars have used QCA with panel data (Nishant and Ravishankar, 2020), we adopt a deductive approach that nicely complements Nishant and Ravishankar's (2020) inductive use of QCA, thus responding to recent calls "for further studies that shed light on longitudinal changes in configurations and underlying reasons for those" (Park & Mithas, 2020: 103).

The remainder of this paper unfolds as follows. Section 2 interweaves the literature of e-Government success with e-Government maturity models to highlight a new maturity model of e-Government success. Section 3 introduces the use of fsQCA with panel data in a deductive fashion. Section 4 analyses our findings for both the presence and absence of high levels of EGDI. Section 5 draws the core theoretical and practical implications of this research while Section 6 concludes this paper and outlines its primary limitations. The Appendix conducts relevant robustness checks to assess the robustness of our findings using different calibration, consistency and frequency thresholds.

The maturity model of e-Government success

E-Government may be conceptualized as the application of Web 2.0 technology to the specific domain of Government (Das et al., 2017). While the demand side of e-Government focuses on the uptake of e-Government services and citizens' satisfaction, the supply side of e-Government is mostly concerned with the obstacles that e-Government projects face and the demands they place on the back-office functions or the back-end of e-Government (Ibid). While some prominent e-Government scholars have argued to switch the focus from the back-end of e-Government to the front-end of e-Government where e-Participation lies at the core of e-Government (Andersen and Henriksen, 2006), other e-Government scholars have called for a dual e-Government construct that takes e-Government development and e-Governance (or e-Participation) together (Calista and Melitski, 2007). Other e-Government scholars have reiterated this argument by stating that IS success metrics should capture both social and traditional, utilitarian values in the context of Web 2.0 e-Government (Scott et al., 2016). By adopting public value theory to expand the DeLone and McLean's (1992; 2003) IS success model, Scott et al (2016), for example, have proposed a broad public value framework that integrates both tangible benefits of improved efficiency/service effectiveness and democratic values of e-Participation. Informed by the view that investments in technological capabilities are not the only contributors to e-Government success, in this paper we propose a maturity model of e-Government success that encompasses both the supply-side (i.e., investments in telecommunication infrastructures, as well as investments in online services and human capital) and the demand-side of e-Government (i.e., e-Participation to boost demand of e-Government services). Accordingly, we set out to investigate the complex interactions between and among supply-side and demand-side factors of e-Government success over time.

Since we define e-Government maturity as both the process and the outcome of the successful enactment of e-Government, in this paper we adopt a longitudinal approach that interweaves fsQCA analysis with panel data to study how e-Government performance changes over time. Drawing on the United Nations' survey data over a period spanning from 2003 to 2020 (United Nations, 2003; 2004; 2005; 2008; 2010; 2012; 2014; 2016; 2018; 2020), we track the progress of e-Government development via the United Nations E-Government Development Index (EGDI) because "the EGDI is a benchmarking tool for e-Government development to be used as a proxy performance indicator" (UN 2020: 11). Though the EGDI is a composite index based on the weighted average of three normalized indices, namely, the Telecommunications Infrastructure Index (TII), the Human Capital Index (HCI) and the Online Service Index (OSI), in this study we broaden our conceptualization of e-Government success (or maturity) to encompass the social value of e-Government initiatives in terms of e-Participation because "Government's willingness to implement e-Participation in a country plays a significant role in affecting its e-Government maturity" (Krishnan et al., 2017: 309). By combining relevant e-Government variables, we respond to Srivastava & Teo's (2008: 85) call for further research aimed at enhancing and developing the concept of e-Government maturity and, therefore, refining our understanding of the relation "between e-Government development and e-Participation" (Ibid: 86). The figure below depicts the maturity model of e-Government success in set-theoretic terms where the interplay of supply-side and demand-side factors generates e-Government performance over time:

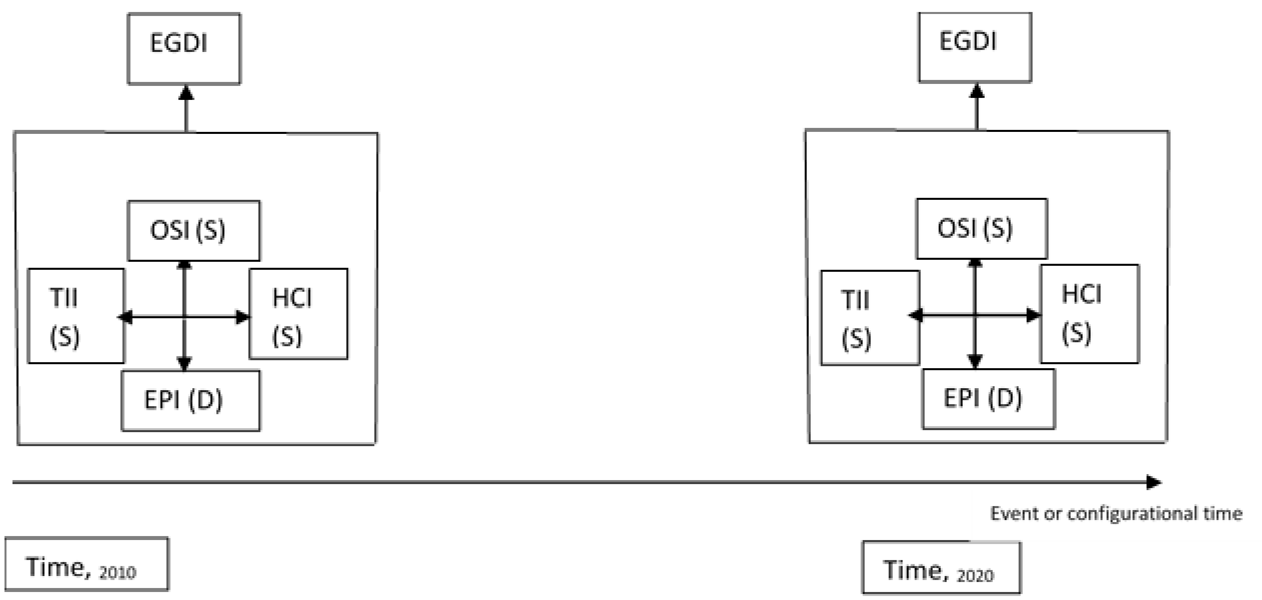

Figure 1: The maturity model of e-Government success (Legend: OSI= Online Service Index; TII= Telecommunication Infrastructure Index; HCI= Human Capital Index; EPI= Electronic Participation Index; S= Supply; D= Demand)

It is worth stressing that while traditional models of IS success embrace the idea of clock time in the horizontal axis, our model is premised on a different view of time, namely event or configurational time, that is a conception of time aimed at capturing configurations of performance variables at distinct time points. Hence, our model is not aligned with one dependent variable, but represents a system of mutually interdependent performance variables that endogenously drive performance outcomes over time (Täuscher, 2018).

Furthermore, the EGDI indices are structured as follows. The TII is the arithmetic average of four indicators: 1) estimated internet users per 100 inhabitants; 2) number of mobile subscribers per 100 inhabitants; 3) active mobile-broadband subscription; 4) number of fixed broadband subscriptions per 100 inhabitants (UN, 2020). The HCI consists of four components: 1) adult literacy rate; 2) the combined primary, secondary and tertiary gross enrolment ratio; 3) expected years of schooling; 4) average years of schooling (Ibid). The e-Participation index (EPI) consists of three separate components that cover: 1) e-information sharing; 2) e-consultation; 3) e-decision making (Ibid). E-Government scholars have defined these three components very broadly. For example, they have defined e-information sharing as the provision of online information including both top-down and bottom-up initiatives (Medaglia, 2012). E-decision making has been defined as the "direct link between participants (e.g., citizens) and the political decision-making process" (Ibid: 351) and e-consultation has been defined as "an activity of providing ICT-enabled feedback mechanisms from citizens to Governments and public agencies" (Ibid: 352). The OSI assesses the extent to which a Government has established an online presence (Krishnan et al., 2017). The OSI differs from the other indices "because it is not composed of multiple normalized indices. Rather, it is calculated by summing the points each country has received (assigned by the UN research team) across different categories (e.g., points for emerging information services, points for enhanced information services, points for transaction services, etc.) and then applying a min–max normalization [sic] However, it is mathematically comparable to the other" indices (Whitmore, 2012: 70). The OSI is based upon the UN's four stage model of online service development which maps the journey "from a Government-centric to a citizen-centric organization, in which e-services are targeted to citizens through life-cycle events and segmented groups to provide tailor-made services" (Krishnan et al., 2017: 311).

Methodology: the use of fsQCA with panel data

We use fsQCA with panel data spanning from 2003 to 2020. While Krishnan et al. (2017) have conducted a cross-sectional analysis based on average scores of the 2010-2012 UN's datasets, this paper extends the analysis to longitudinal (panel) data spanning the 2003-2020 period considering that "at least nine years of data are required to support a robust estimation of empirical specifications while performing panel data analysis (especially in the context of country-level analysis)" (Ibid: 309). Considering that the UN dataset is available from 2003, we decided to use 2003 as the starting year in our dataset to trace the effects of configurational changes over time.

Our data collection and analysis proceeded in two steps. We first downloaded the country data from the UN's e-Government knowledge base for the period spanning from 2003 to 2020 (UN, 2003; 2004; 2005; 2008; 2010; 2012; 2014; 2016; 2018; 2020). In the second step, we used fsQCA (Ragin, 2000; 2009) to investigate which causal conditions lead countries to high levels of e-Government performance and the way these conditions combine to achieve high levels of e-Government performance over time. QCA is a case-oriented methodology that combines cross-case comparative research with set-theoretic methods (Schneider and Wagemann, 2012). "To do so, QCA treats each case as a member of multiple sets and conceives both conditions and outcome as sets" (Aversa et al., 2015: 661). QCA is ideally suited to address our research questions because "it starts by assuming maximum causal complexity and then mounts an assault on that complexity" (Ragin, 1987: X) in order to identify multiple configurations of causal conditions that lead to the outcome of interest in a simpler and more theoretically-plausible fashion. Though prior applications of QCA with panel data have used its crisp-set version where each case is coded as either "in" or "out" of a set (Aversa et al., 2015; Nishant and Ravishankar, 2020), in this paper we use the fuzzy-set version of QCA (fsQCA) because of two main reasons: first, the UN's dataset includes variables that have been normalized along the 0-1 continuum; second, we followed Ragin's (2009: 141) advice that researchers should not use crisp sets if they "can represent their causal conditions and outcomes as fuzzy sets."

QCA uses a particular coding procedure (called "calibration") to transform the causal and outcome variables into fuzzy-set membership scores. Since the UN's e-Government survey uses the quartiles to rank order the performance of individual countries, we used three conventional "anchor points" as meaningful cut-off values (Ragin, 2009), namely, 0.75 (cut-off value for full-membership in the target set), 0.499 (cut-off value for the cross-over point separating cases that are more in versus more out of the target set) and 0.25 (cut-off value for full non-membership in the target set). For example, a given country can be coded as a member of the group of countries with high e-Government performance (coded as 0.75), as a non-member of the group of countries with high e-Government performance (coded as 0.25) or somewhere in between full membership or full non-membership (where 0.499 represents the point of maximum ambiguity or fuzziness).

Starting from the calibrated data, the fsQCA program generates a "truth-table" that lists the logically-possible configurations of causal conditions with their respective frequency number and consistency score (Ragin and Davey, 2016). While consistency (sufficiency) measures the degree to which the configuration of causal conditions (i.e., the empirical data) is a subset of the outcome of interest, the frequency number indicates the number of cases that replicate a specific configuration. Following standards of good practice, we set a consistency threshold of 0.80 ("almost always sufficient") and a frequency threshold of 3+ (Greckhamer et al., 2013: 54).[1] Although the fsQCA program generates three solutions, that is, three statements about one or multiple combinations of causal conditions, in this paper we report only the intermediate solutions because they strike a balance between complexity (no minimization is allowed to eliminate redundant causal conditions) and parsimony (full minimization is allowed to eliminate redundant causal conditions). As such, the intermediate solution is the "preferred solution" because it is "often the most interpretable" solution (Ragin, 2009: 175). Given that this paper is primarily concerned with the change of e-Government performance (measured with the EGDI index) over time, the relationship between the components of e-Government performance and e-Government performance itself is underpinned by multiple configurations of causal conditions that jointly lead to high levels of e-Government performance over time (i.e., from 2003 to 2020). Hence, the primary focus of this paper is on configurational changes across time, that is, changes in the combinations of causal conditions leading to high levels of e-Government performance over time. By charting how the configurations of performance variables change over time, we plan to capture the demand-side and supply-side factors that endogenously drive performance outcomes over time.

QCA is both a research approach and a set of techniques for data analysis (Schneider and Wagemann, 2012). As a research approach, QCA formalizes how different conditions combine to produce a qualitative change (Ragin, 1987). Viewed as a research approach (or strategy), QCA encompasses four main components. First, it views cases as holistic configurations of causal conditions. "The organizing idea is that the parts of a case constitute a coherent whole and the effects of variables should be assessed in the context of the case and not detached from it [sic] The essence of the analytic approach is to link configurations of causally relevant conditions to outcomes" (Ragin, 2014: XXI). Second, the approach is comparative "because it enables researchers to explore similarities and differences across comparable cases" (Ibid). Third, QCA aims at developing an explanatory model through an iterative "dialogue between theory and evidence" (Ibid). Fourth, QCA "implements a context-specific notion of causality" (Ibid: XXII). This, in turn, implies that a given condition may have opposite effects depending on context, that is, depending on its combination with other causal conditions so much so that "several different combinations of conditions may produce the same outcome" (Ibid).

As a group of techniques, QCA entails three steps. First, causal conditions and the outcome of interest must be calibrated (or scored) through the assignment of appropriate set-membership scores based on specific anchor points (Ragin, 2009). Second, the outcome value for each truth-table row is determined based on the minimum number of cases required for a solution (that is, the frequency threshold) and, for those rows populated with cases, pre-agreed consistency (sufficiency) thresholds which should not go below 0.75 (Ragin, 2009: 136/144), thus ensuring that each such row is a consistent subset of the outcome.[2] Third, the truth table should be minimized using appropriate software (e.g., the fsQCA 3.0 software program) to produce the intermediate solution on the basis of theoretically-plausible assumptions (Ragin and Davey, 2016).

---

[1] We also looked at the Proportional Reduction in Inconsistency (PRI) scores to detect simultaneous subset relations with the outcome and the lack of the outcome by setting a cut-off threshold of 0.65 in accordance with prior research (Cf. Greckhamer, 2016: 802).

[2] Please note that in this paper we used a more demanding consistency (sufficiency) threshold of 0.80 in accordance with standards of good practice (Cf. Greckhamer et al., 2013: 54). We also used a PRI threshold of 0.65 to further strengthen our findings (Cf. Greckhamer, 2016: 802).

Analysis of findings

The core feature of fsQCA techniques is to run the analysis both for the presence (1) and absence of the outcome (0). Indeed, an important insight of fsQCA techniques is causal asymmetry, that is, quite often the conditions associated with the presence of the outcome (e.g., high levels of e-Government performance) are very different from those associated with its absence (e.g., low levels of e-Government performance) (Cf. Fiss, 2011). Accordingly, we now proceed with the fsQCA analysis both for high levels of e-Government performance and low levels of e-Government performance. Tables 1 and Table 2 below display the multiple configurations that, over the 2003-2020 period, lead to high levels of e-Government performance and low levels of e-Government performance respectively.

Years	**2003**		**2004**	**2005**	**2008**	**2010**		**2012**		**2014**		**2016**		**2018**		**2020**	
Solutions/Configurations	S_1	S_2	S_1	S_1	S_1	S_1	S_2	S_1	S_2	S_2	S_{3a}	S_2	S_{3b}	S_2	S_{3c}	S_2	S_{3c}
EPI											●		⬤		⬤		⬤
OSI	⬤		⬤	⬤	⬤	⬤		⬤			⬤		⬤		●		●
HCI	●	●	●	●	●	●	●	●	●	●	⬤	●	⬤	●	⬤	●	⬤
TEL		⬤					⬤		⬤	⬤		⬤		⬤		⬤	
Raw Coverage	0.60	0.42	0.69	0.74	0.70	0.50	0.43	0.75	0.56	0.68	0.65	0.66	0.80	0.67	0.88	0.86	0.82
Unique Coverage	0.25	0.07	0.69	0.74	0.70	0.19	0.12	0.28	0.08	0.20	0.17	0.09	0.24	0.04	0.26	0.13	0.09
Consistency	0.95	1.00	0.94	0.92	0.95	0.98	1.00	0.96	0.98	0.98	0.96	0.99	0.95	1.00	0.95	0.98	0.97
Solution Coverage	0.68		0.69	0.74	0.70	0.62		0.83		0.85		0.89		0.93		0.95	
Solution Consistency	0.96		0.94	0.92	0.95	0.98		0.95		0.95		0.95		0.95		0.96	
Representative cases. Please note that we regarded Singapore and Rep. of Korea as developed countries. Furthermore, we take Bahrain & Kazakhstan as	Developed countries and a few developing countries (e.g., Argentina and Brazil*) *Only represent		Developed countries and a few developing countries (e.g., Argentina and	Developed countries and a few developing countries (e.g., Argentina and	Developed countries and a few developing countries (e.g., Argentina, Bahrai	Developed countries and a few developing countries (e.g., Bahrain and Kazakhstan as		Developed countries and a few developing countries (e.g., Bahrain and Kazakhstan as		Developed countries and a few developing countries (e.g., Bahrain and Kazakhstan as		Developed countries and a few developing countries (e.g., Bahrain and Kazakhstan as		Developed countries and a few developing countries (e.g., Bahrain and Kazakhstan as		Developed countries and a few developing countries (e.g., Bahrain and Kazakhstan as	

instances of developing high-income and middle-income countries that belong to the high-EGDI set.	ative of S_1. However, both cases are deviant consistency in degree cases (Cf. Oana et al., 2021: 180-200).	Brazil *) *Both cases are deviant consistency in degree cases Cf. Oana et al., 2021: 180-200).	Brazil *) **Both cases are deviant consistency in degree cases Cf. Oana et al., 2021: 180-200).	n and Brazil *) Brazil is a deviant consistency in degree case Cf. Oana et al., 2021: 180-200).	typical cases*) *Kazakhstan is only representative of S_1	typical cases*) *Kazakhstan is only representative of S_1	typical cases)	typical cases)	typical cases)	typical cases)

Table 1: Multiple configurations leading to high levels of e-Government performance over time

Year	**2003**	**2004**	**2005**	**2008**	**2010**	**2012**	**2014**		**2016**		**2018**		**2020**	
Solutions/Configurations	S_{4a}	S_{4b}	S_{4b}	S_{4b}	S_5	S_{4a}	S_6	S_{4c}	S_6	S_{4d}	S_6	S_{4c}	S_6	S_{4c}
EPI	⊗	⊗	⊗	⊗	⊗	⊗		⨂		⨂		⨂		⨂
OSI	⨂	⨂	⨂	⨂	⊗	⨂		⊗		⨂		⊗		⊗
HCI					⨂		⨂		⨂		⨂		⨂	
TEL	⨂	⊗	⊗	⊗	⊗	⨂	⊗	⨂	⊗	⨂	⊗	⨂	⊗	⨂
Raw Coverage	0.98	0.97	0.95	0.96	0.24	0.95	0.46	0.92	0.52	0.87	0.55	0.81	0.57	0.84
Unique Coverage	0.98	0.97	0.95	0.96	0.24	0.95	0.02	0.47	0.04	0.40	0.11	0.36	0.07	0.33
Consistency	0.89	0.89	0.89	0.86	1.00	0.86	1.00	0.92	1.00	0.94	0.99	0.93	0.99	0.94
Solution Coverage	0.98	0.97	0.95	0.96	0.24	0.95	0.93		0.91		0.91		0.90	
Solution Consistency	0.89	0.89	0.89	0.86	1.00	0.86	0.92		0.94		0.94		0.95	
Representative cases. Please note that Somalia is an instance of a low-income developing country.	Somalia (typical)	Somalia (typical)	Somalia (typical)	Somalia (typical)	Somalia (typical)	Somalia (typical)	Somalia (typical)		Somalia (typical)		Somalia (typical of S_6 but deviant consistency in degree of S_4c)		Somalia (typical of S_4c but deviant consistency in degree of S_6)	

Table 2: Multiple configurations leading to low levels of e-Government performance over time

Although Table 1 shows that there are multiple configurations leading to high levels of e-Government performance, the configuration consisting of investments in telecommunication infrastructure combined with investments in human capital stands out (S2) as, with the exception of the 2004-2008 period, this configuration points to a consistent pattern (see the S2 configuration highlighted with the grey shade). This finding, in turn, is in line with extant research that suggests that "through investments in technological and human capabilities, it might be possible for a country to move up the ladder of e-Government maturity" (Krishnan et al., 2017: 309). Indeed, although being peripheral in this particular configuration of causal conditions, investments in human capital are a necessary condition for high levels of e-Government performance across the whole period under investigation (please see the Appendix for relevant details). Far from working alone, these investments in human capital produce a synergistic effect when combined with investments in telecommunication infrastructure because they ensure that the right mix of capabilities and skills is in place to maximize the return from investing in mobile-broadband infrastructure, as well as internet infrastructure. Hence, investments in technological infrastructure and human capabilities combine synergistically to produce high levels of e-Government performance.

Nevertheless, the fact that there is equifinality, that is, multiple configurations of causal conditions leading to the same outcome, is reassuring because it shows that the same level of e-Government performance (or maturity) may be reached using different recipes (or configurations). For example, in the years spanning from 2003 to 2012, investments in human capital can produce synergistic effects when combined with investments in online services, thus showing a different pathway to e-Government maturity from the one highlighted in grey in Table 1 (Cf. S1 versus S2). Likewise, in 2014 with the emergence of social media as a new channel for Government-to-Citizens (G2C) communications, we witness the emergence of a new path to e-Government maturity, namely e-Participation in combination with human capital investments and online services investments (Cf. S3a with S1 and S2 in Table 1). Furthermore, from 2016 onwards, e-Government Participation moves to the core of Solution S3 so much so that it becomes a core feature of solution S3b in 2016 and solution S3c in 2018 and 2020. Ultimately, the 2014-2020 findings point to high levels of e-Government performance stemming either from investments in telecommunication infrastructures and human capital or from the delivery of a wide range of online services "supported by whole-of-Government and whole-of-society engagement and integration [sic] and the expansion of e-Participation and partnerships [sic] and the strengthening of digital capacities (or human capabilities/skills) to deliver people-centric services" (UN, 2020: XXIII).

Furthermore, the analysis of low levels of EGDI displays the notion of causal asymmetry in action. While configuration S2 stood out in the analysis of high levels of EGDI, it turns out that the recipes leading to low levels of EGDI are not the mirror image of S2 with reversed signs. Indeed, the configurations for low EGDI levels require the lack of investments in telecommunication infrastructure combined with the lack of e-Participation and the lack of online services (see configuration S4). With the exception of 2010 (i.e., configuration S5) and the marginal empirical importance of configuration S_6, configuration S4 stands out in the analysis of negative cases. Likewise, while investments in human capital are a necessary condition for high EGDI throughout the 2003-2020 period, it turns out that the lack of investments in telecommunication infrastructure is the necessary condition for low EGDI levels in this period, thus displaying causal asymmetry once again (please see the Appendix for relevant details).

Discussion

Spurred by partially-conflicting findings regarding the role that human capital plays as a contributor to e-Government maturity (Cf. Das et al. 2017: 422; Krishnan et al., 2017: 308), in this paper we have demonstrated that human capital works in combination with many other causal conditions to contribute to high levels of e-Government performance and, indirectly, e-Government maturity. We have also demonstrated that, although there are multiple configurations of causal conditions contributing to the outcome of interest at each time point (2003; 2004; 2005; 2008; 2010; 2012; 2014; 2016; 2018; 2020), the configurations leading to high levels of e-Government performance are markedly different from those leading to low levels of e-Government performance (Cf. Table 1 vs. Table 2). Furthermore, with the exception of the period 2004-2008, the configuration entailing investments in technological infrastructure and human capital stands out throughout the period under investigation. These findings have significant implications for e-Government research.

First, these findings challenge the view that e-Government maturity is characterized by a singular recipe for e-Government performance. Indeed, countries may enact multiple configurations of e-Government performance (or maturity) at once. For example, while the most successful countries implemented simultaneously both investments in human capital and in integrated telecommunication infrastructures in the period ranging from 2010-2020 (see S2), these very same countries switched paths from investments in online services and human capital in the 2010-2012 period (S1) to more advanced stages of e-Participation from 2014 onwards (see configurations S3a, S3b, S3c where e-Participation is core from 2016 onwards). The UN (2014: 28) report confirms this finding: "The use of social media by Governments is also increasing fast with the number more than tripling from 2010 to 2012 and with another 50 per cent rise in 2014, so that today 118 countries use it for e-consultation and 70 for e-Government generally [sic] In this context, both mobile and social media are becoming more important both to deliver services and to interact with users in a variety of ways." Furthermore, the analysis of negative cases reveals asymmetric findings considering that the recipes leading to low levels of e-Government performance are not the opposite of those leading to high EGDI. Indeed, while one solution term S6 is the coarse opposite of configuration S2, it turns out that configuration S4 is not the reverse of configuration S3 because countries, in general, were "putting more investment in human capital as compared to ICT infrastructure" (UN, 2014: 38). Nevertheless, the configurations leading to low levels of EGDI do show the relevance of the lack of investments in telecommunication infrastructure considering that the absence of these investments is a relevant necessary condition for low EGDI levels (please see the Appendix for relevant details).

Another important insight stemming from our research is that e-Government success and, therefore, e-Government maturity is a "configural/configurational construct" (Wang, 2021), that is, a complex, multifaceted construct emerging from heterogeneous configurations of causal conditions. Far from involving the same causal conditions in each instance of the outcome, each configuration instantiates a heterogeneous combination of causal conditions that "fits" or "coheres" within the context under investigation. For example, while configurations S1 and S2 fit with an environment characterized by pronounced investments in online services and technological infrastructure respectively (see these recipes' core conditions in Table 1), configuration S3c fits within an environment where e-Participation and investments in human capital are key (again, see these recipes' core conditions in Table 1). The UN (2010; 2012) reports support these findings as back in 2010-2012, the use of Web 2.0 tools on Government portals and websites was "at its infancy stage" (UN, 2010: 102) and, therefore, e-Participation was "in a nascent state in many countries" (UN, 2010: 18) so much so that "the explosive growth of broadband access in developed regions and mobile cellular subscriptions in developing countries" (Ibid: 17) including significant advances in "online services" (Ibid: 17) were the key determinants of successful e-Government enactment. Likewise, the UN (2012: 21) report reiterates that "only 40 per cent of Member States" were using a social networking site so much so that the vast majority of countries were "offering low levels of engagement possibilities" (Ibid). To reiterate, the situation changed rapidly from 2014 onwards with the more intensive use of social media by Governments both as a form of e-Consultation and e-Government more generally.

To be sure, the transition from an environing context (Avgerou, 2019) characterized by investments in online services to an environing context characterized by e-Participation and investments in human capital is a smooth transition considering that investments in online services play a core causal role in the transition period ranging from 2014 to 2016. While transitions may portray regular stages of e-Government maturity, they may also point to more radical shifts that may redirect paths of e-Government maturity (Abbott, 2001). Accordingly, we also identified more radical changes (or turning points) that interrupted regular patterns of e-Government maturity, thus switching the maturity process to a faster or slower pace of technological development. The UN (2010: 17) report, for example states: "middle-income countries in particular have made significant advances, to the point where a number of them have usurped positions held in the past by high-income countries in the e-Government development index." Likewise, the UN (2012: 28) report states that "some of the developing countries have found ways to leapfrog traditional development cycles by deploying mobile technology for bridging the digital divide. They have reoriented their public sector governance systems towards user-centric approaches visible on their websites through multichannel service delivery features."

Figure 2 depicts two separate models of change, namely incremental models of change (typical of developed countries – see the dashed black line representing high EDGI countries) and punctuated equilibrium models (typical of middle-income and developing countries – see Bahrain, Kazakhstan and Somalia). Taking Bahrain, Kazakhstan and Somalia as instances of cases lying at the two opposite ends of the high-EGDI (i.e., Bahrain and Kazakhstan) versus low-EGDI continuum (i.e., Somalia), it is possible to highlight an incremental process of change punctuated by radical shifts or turning points identified through visual interpretation. Indeed, Bahrain "improved significantly since the 2005 survey" (UN, 2008: 35) whereas Kazakhstan experienced a turning point in 2008 when it continued to lead the Central Asia region while "the countries in this region had a lower e-Government readiness index than in 2005 because they did not enhance their sites" (UN, 2008: 31). Furthermore, Kazakhstan adopted in 2012/13 'Information Kazakhstan – 2020' "to create conditions for its transition to an information society" (UN, 2018: 174), thus approaching the European EGDI levels in 2012. Likewise, Somalia experienced a turning point in 2014 when the disparity in terms of internet use between developed and developing countries was most pronounced (UN, 2014: 126).

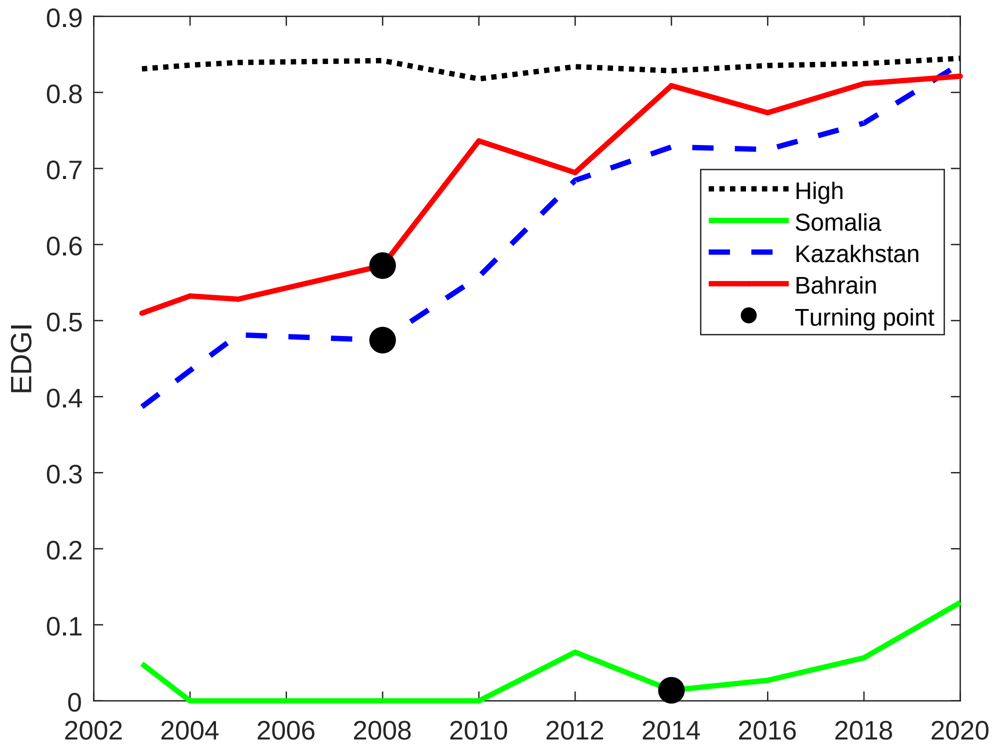

Figure 2 The trajectory-turning point model. Legend: High-EGDI Countries' Trajectory (Dashed black line); Bahrain's trajectory (Solid red Line); Kazakhstan's trajectory (Dashed dark-blue trajectory); Somalia's trajectory (Solid green line). Turning points are identified through visual interpretation.

The Kazakhstan's case is of particular interest considering that it challenges the view of e-Government maturity as a regular trajectory of incremental stages of e-Government development. While existing studies embody "a model of progressive development, in fact ICT take-up in Government does not necessarily follow a straight path" (UN, 2014: 69) considering that developing and middle-income countries may experience turning points that are bound to switch trajectories unexpectedly. The UN (2020: 97) report confirms this insight: "Moving up ten or more positions in the EGDI ranking typically represents significant e-Government development; Land-locked and Developing Countries (LLDCs) that have achieved such progress in 2020 include Armenia, Bhutan, Paraguay, Kazakhstan and Botswana."

Furthermore, each "time point" along the 2003-2020 period marks a system of mutually-interdependent performance variables that endogenously drive performance outcomes over time (i.e., high EGDI). To reiterate, this finding challenges the idea that there is one perfect mix of causal conditions to the envisioned end state (i.e., keeping up with the pace of technological change). Rather, e-Government maturity corresponds to multiple enactments of e-Government at each "time point" and, therefore, e-Government maturity is characterized by multiple configurations at once.

Though extant studies describe e-Government maturity as an envisioned end state characterized by a sequential and irreversible process of change (Poeppelbuss et al., 2011), it turns out that this change process may be both unpredictable and equifinal. Furthermore, the progression towards e-Government maturity is underpinned by dialectical mechanisms that produce tensions (e.g., the tension between investing resources to reach a desired end state and facing unanticipated challenges such as "outdated policies, budgetary constraints, inadequate technical skills and lack of leadership" (UN, 2012: 96; see also UN, 2014: 32/99). Bahrain is a case in point. Despite being a member of the set (or group) of countries with high EGDI in 2010, 2012, 2014, 2016 and 2018, Bahrain has dropped out from this set of countries in 2020 (when its overall EGDI ranking dropped to 38 from a high of 13 in 2010). Likewise, Kazakhstan itself "has improved from 2010 in terms of providing online features that allow citizens to engage with Government" (UN, 2012: 59) so much so that it has joined the set of countries with high EGDI in 2012 and 2014 only to drop out of this set soon thereafter and managing a comeback in 2020, thus exhibiting a "more rapid increase in EGDI values" in 2020 (UN, 2020: 76). Though Kazakhstan has approached Europe's average EGDI level in 2012, its overall pace of e-Government development has slowed down since 2012 considering that "laws and regulations governing electronic transactions" in Kazakhstan remained weak until 2020 (UN, 2020: 72) with a knock-on effect on Kazakhstan's ability to provide transactional services. Furthermore, Kazakhstan has a highly developed human capital, but the state of its infrastructure "may be impeding further progress in e-Government development" (UN, 2020: 21), thus slowing down the overall pace of e-Government development. Not only does Figure 2 above corroborate the idea of equifinality considering that one and the same country can enact multiple configurations of high levels of e-Government development at once. It also underscores the idea of multifinality, that is, one configuration leading to multiple outcomes across different time points (e.g., investments in human capital and telecommunication infrastructure leading to high EGDI in 2003, 2010, 2012, 2014, 2016, 2018 and 2020).

Conclusion

Drawing on the fsQCA analysis of the UN EGDI panel data spanning the 2003-2020 period, this paper makes a threefold contribution to e-Government research. First, it shows that e-Government maturity is a complex, multifaceted construct encompassing both temporal (i.e., longitudinal aspects) and causal dimensions that conjointly affect the outcome of interest (i.e., e-Government performance). In particular, this paper shows that causes work in conjunction with each other rather than separately to produce the outcome of interest. Second, our contribution leverages the idea of equifinality (i.e., multiple paths leading to high EGDI) by showing two models of change working in parallel, namely incremental models of change (typical of developed countries) and punctuated equilibrium models (typical of developing and middle-income countries). Using Abbott's trajectory-turning point model, we show that while developed countries feature regular trajectories of e-Government development based on an incremental process of change, developing and middle-income countries are constantly struggling to keep up with the pace of technological change only to be disrupted by sudden and unexpected turning points. This, in turn, suggests a punctuated equilibrium model of change for developing and middle-income countries where the envisioned end state (i.e., keeping up with the pace of technological change) is constantly being disrupted by sudden and unexpected shocks that may shift the process downwards towards a slower pace of technological development, or, at times, upwards towards a faster pace of technological change. Furthermore, this finding has noteworthy implications for policy-making because it suggests that e-Government maturity is more unpredictable in developing countries. Therefore, we recommend that, within developing countries, policy makers focus on those configurations with the largest unique coverage as they are more important from an empirical perspective (Ragin, 2006). Third, and last, this study showcases the use of fsQCA with panel data in a deductive fashion to highlight "common transitions, evolutionary trajectories, and movements between stages of a life cycle" (Miller 2018: 462). Though extant research has advocated an inductive use of QCA with panel data (Nishant and Ravishankar, 2020), we showcase a deductive approach that interweaves incremental and radical processes of change in a longitudinal fashion, thus responding to recent calls "for further studies that shed light on longitudinal changes in configurations and underlying reasons for those" (Park & Mithas, 2020: 103).

Several limitations plague our findings. In particular, the composition of the indicators of the EGDI has changed over time, thus undermining the robustness of our comparative analysis. For example, the telecommunication infrastructure index included, in the early years, such indicators as TV ownership and the density of fixed-lines telephone which were subsequently dropped because of their lack of relevance to modern e-Government services. Furthermore, the use of standardized cut-off thresholds for Consistency (sufficiency), PRI scores and frequency thresholds does not account for gaps in these thresholds, let alone contextual differences between developed and developing countries. Lastly, the claims of causality in this paper should be taken with a grain of caution as we neither studied lagged effects nor did we use a specific theoretical framework to model causality. Despite these limitations, our findings could be beefed up by including other conditions not considered in this study such as the presence (or absence) of robust ICT laws and corruption (Khan & Krishnan 2019; Khan et al., 2020; Silal et al., 2019). Therefore, we invite e-Government scholars to broaden our model in future studies of e-Government maturity in order to do justice to its configurational attributes.

References

Abbott, A. (2001). Time matters: On theory and method, Chicago: University of Chicago Press.

Andersen, K. V., & Henriksen, H. Z. (2006). E-government maturity models: Extension of the Layne and Lee model. Government Information Quarterly, (23: 2), pp. 236-248.

Aversa, P., Furnari, S., & Haefliger, S. (2015). Business model configurations and performance: A qualitative comparative analysis in Formula One racing, 2005–2013. Industrial and Corporate Change, (24:3), pp. 655-676.

Avgerou, C. (2019). Contextual explanation: Alternative approaches and persistent challenges. MIS Quarterly, (43: 3), pp. 977-1006.

Bititci, U. S., Garengo, P., Ates, A., & Nudurupati, S. S. (2015). Value of maturity models in performance measurement. International Journal of Production Research, (53: 10), pp. 3062-3085.

Das, A., Singh, H., & Joseph, D. (2017). A longitudinal study of e-government maturity. Information & Management, (54: 4), pp. 415-426.

Dawson, G. S., Denford, J. S., Williams, C. K., Preston, D., & Desouza, K. C. (2016). An examination of effective IT governance in the public sector using the legal view of agency theory. Journal of Management Information Systems, (33: 4), pp. 1180-1208.

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. Information Systems Research, (3: 1), pp. 60-95.

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: a ten-year update. Journal of Management Information Systems, (19: 4), pp. 9-30.

El Sawy, O. A., Malhotra, A., Park, Y., & Pavlou, P. A. (2010). Research commentary—seeking the configurations of digital ecodynamics: It takes three to tango. Information systems research, (21: 4), pp. 835-848.

Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. Academy of Management Journal, (54: 2), pp. 393-420.

Greckhamer, T. (2016). CEO compensation in relation to worker compensation across countries: The configurational impact of country□level institutions. Strategic Management Journal, (37: 4), pp. 793-815.

Greckhamer, T., Misangyi, V. F., & Fiss, P. C. (2013). The two QCAs: From a small-N to a large-N set theoretic approach. In Configurational theory and methods in organizational research, Bingley, UK: Emerald Group Publishing Limited.

Khan, A., & Krishnan, S. (2019). Conceptualizing the impact of corruption in national institutions and national stakeholder service systems on e-government maturity. International Journal of Information Management, 46, 23-36.

Khan, A., Krishnan, S., & Arayankalam, J. (2020). The role of ICT laws and national culture in determining ICT diffusion and well-being: A cross-country examination. Information Systems Frontiers (24: 2), pp. 415-440.

Klievink, B., & Janssen, M. (2009). Realizing joined-up government—Dynamic capabilities and stage models for transformation. Government Information Quarterly, (26: 2), pp. 275-284.

Krishnan, S., Teo, T. S., & Lymm, J. (2017). Determinants of electronic participation and electronic government maturity: Insights from cross-country data. International Journal of Information Management, (37: 4), pp. 297-312.

Lasrado, L., Vatrapu, R., Andersen, K.N., 2015. Maturity Models Development in IS Research: A Literature Review. Selected Papers of IRIS, Issue Nr 6. Retrieved from <http://aisel.aisnet.org/iris2015/6> (access date: 04/08/2022).

Layne, K., & Lee, J. (2001). Developing fully functional E-government: A four stage model. Government Information Quarterly, (18: 2), pp. 122-136.

Lee, J. (2010). 10 year retrospect on stage models of e-Government: A qualitative meta-synthesis. Government Information Quarterly, (27: 3), pp. 220-230.

Miller, D. (2018). Challenging trends in configuration research: Where are the configurations? Strategic Organization, (16: 4), pp. 453-469.

Misangyi, V. F., Greckhamer, T., Furnari, S., Fiss, P. C., Crilly, D., & Aguilera, R. (2017). Embracing causal complexity: The emergence of a neo-configurational perspective. Journal of Management, (43: 1), pp. 255-282.

Medaglia, R. (2012). eParticipation research: Moving characterization forward (2006–2011). Government Information Quarterly, (29: 3), pp. 346-360.

Nishant, R., & Ravishankar, M. N. (2020). QCA and the harnessing of unstructured qualitative data. Information Systems Journal, (30: 5), pp. 845-865.

Oana, I. E., Schneider, C. Q., & Thomann, E. (2021). Qualitative Comparative Analysis using R: A beginner's guide. Cambridge University Press.

Park, Y., & Mithas, S. (2020). Organized Complexity of Digital Business Strategy: A Configurational Perspective. MIS Quarterly, (44: 1), pp. 85-127.

Park, Y., Fiss, P. & El Sawy, O A. (2021). "Theorizing the Multiplicity of Digital Phenomena: The Ecology of Configurations, Causal Recipes, and Guidelines for Applying QCA.". MIS Quarterly, (44: 4), pp. 1493-1520.

Pittaway, J. J., & Montazemi, A. R. (2020). Know-how to lead digital transformation: The case of local governments. Government Information Quarterly, (37: 4), pp. 1-15.

Poeppelbuss, J., Niehaves, B., Simons, A. & Becker, J. (2011). Maturity models in information systems research: literature search and analysis Communications of the Association for Information Systems, (29: 27), pp. 505-532.

Ragin, C. C. (1987/2014). The comparative method: Moving beyond qualitative and quantitative strategies, Berkeley: University of California Press.

Ragin, C. C. (2000). Fuzzy-set social science, Chicago: University of Chicago Press.

Ragin, C. C. (2006). Set relations in social research: Evaluating their consistency and coverage. Political analysis, (14:3), pp. 291-310.

Ragin, C. C. (2009). Redesigning social inquiry: Fuzzy sets and beyond, Chicago: University of Chicago Press.

Ragin, C., & Davey, S. (2016). Fuzzy-Set/Qualitative Comparative Analysis 3.0. Irvine, California: Department of Sociology, University of California.

Schneider, C. Q., & Wagemann, C. (2012). Set-theoretic methods for the social sciences: A guide to qualitative comparative analysis, Cambridge: Cambridge University Press.

Scott, M., DeLone, W., & Golden, W. (2016). Measuring eGovernment success: a public value approach. European Journal of Information Systems, (25: 3), pp. 187-208.

Silal, P., Jha, A., & Saha PhD, D. (2019). From E-Government to good governance: The mediating role of Government E-participation. ICIS Proceedings: https://aisel.aisnet.org/icis2019/digital_government/digital_government/6

Srivastava, S. C., & Teo, T. S. (2008). The relationship between e-government and national competitiveness: The moderating influence of environmental factors. Communications of the association for information systems, (23: 1), pp. 73-94.

Täuscher, K. (2018). Using qualitative comparative analysis and system dynamics for theory-driven business model research. Strategic Organization, (16: 4), pp. 470-481.

United Nations (UN) E-Government Survey 2010 -2020. U.N. Publishing Section, New York (2010-2020).

Wang, P. (2021). "Connecting the Parts with the Whole: Toward an Information Ecology Theory of Digital Innovation Ecosystems," MIS Quarterly (45:1), pp. 397-422.

Whitmore, A. (2012). A statistical analysis of the construction of the United Nations E-Government Development Index. Government Information Quarterly, (29: 1), pp. 68-75.

Appendix

Robustness checks

2003: CALIBRATION THRESHOLDS: EPI/HCI: No upper or lower bound for exclusion and inclusion, but crossover point fixed at 0.49 OSI/TEL: No upper bound for inclusion, but exclusion and crossover fixed at 0.25 and 0.49 respectively CONSISTENCY RANGE: Raw Consistency T.: Lower bound 0.75 Threshold 0.8 Upper bound 0.94 (regardless of pri) The results reported in the paper can also be obtained by changing the pri from 0.51 to 0.82 FREQUENCY RANGE: N.Cut: Lower bound 1 Threshold 3 Upper bound 4
2004: CALIBRATION THRESHOLDS: EPI/HCI/TEL: No upper or lower bound for exclusion and inclusion, but crossover fixed at 0.49 OSI: No upper bound for inclusion, but exclusion and crossover fixed at 0.25 and 0.49 respectively CONSISTENCY RANGE: Raw Consistency T.: Lower bound 0.75 Threshold 0.8 Upper bound 0.91 (regardless of pri) The results reported in the paper can also be obtained by changing the pri from 0.65 to 0.78 FREQUENCY RANGE: N.Cut: Lower bound 2 Threshold 3 Upper bound 21
2005: CALIBRATION THRESHOLDS: EPI/TEL: No upper or lower bound for exclusion and inclusion, but crossover fixed at 0.49 OSI: No upper bound for inclusion, but exclusion and crossover fixed at 0.25 and 0.49 respectively HCI: No upper bound for exclusion and inclusion, but crossover fixed at 0.49 CONSISTENCY RANGE: Raw Consistency T.: Lower bound 0.75 Threshold 0.8 Upper bound 0.9 (regardless of pri) The results reported in the paper can also be obtained by changing the pri from 0.65 to 0.79 FREQUENCY RANGE: N.Cut: Lower bound 2 Threshold 3 Upper bound 26
2008: CALIBRATION THRESHOLDS: EPI/TEL: No upper or lower bound for exclusion and inclusion, but crossover fixed at 0.49 OSI: No upper bound for inclusion, but exclusion and crossover fixed at 0.25 and 0.49 respectively HCI: No upper bound for inclusion and no lower bound for exclusion, but crossover fixed at 0.49 CONSISTENCY RANGE: Raw Consistency T.: Lower bound 0.75 Threshold 0.8 Upper bound 0.93 (regardless of pri) The results reported in the paper can also be obtained by changing the pri from 0.65 to 0.80 FREQUENCY RANGE: N.Cut: Lower bound 3 Threshold 3 Upper bound 24
2010: CALIBRATION THRESHOLDS: EPI/HCI: No upper or lower bound for exclusion and inclusion, but crossover fixed at 0.49 OSI/TEL: No upper bound for inclusion, but exclusion and crossover fixed at 0.25 and 0.49 respectively CONSISTENCY RANGE: Raw Consistency T.: Lower bound 0.75 Threshold 0.8 Upper bound 0.97 (regardless of pri) The same results reported in the paper can be obtained by changing the pri from 0.65 to 0.89 FREQUENCY RANGE: N.Cut: Lower bound 3 Threshold 3 Upper bound 7
2012: CALIBRATION THRESHOLDS: EPI/HCI: No upper or lower bound for exclusion and inclusion, but crossover fixed at 0.49 OSI/TEL: No upper bound for inclusion, but exclusion and crossover fixed at 0.25 and 0.49 respectively CONSISTENCY RANGE: Raw Consistency T.: Lower bound 0.75 Threshold 0.8 Upper bound 0.95 (regardless of pri) The results reported in the paper can also be obtained by changing the pri from 0.65 to 0.87 FREQUENCY RANGE: N.Cut: Lower bound 2 Threshold 3 Upper bound 9
2014: CONSISTENCY THRESHOLDS:

EPI/TEL: No upper bound for inclusion, but exclusion and crossover fixed at 0.25 and 0.49 respectively OSI: No upper bound for inclusion and exclusion, but crossover fixed at 0.49 HCI: No upper or lower bound for exclusion and inclusion, but crossover fixed at 0.49 CONSISTENCY RANGE: Raw Consistency T.: Lower bound 0.44 Threshold 0.8 Upper bound 0.86 (regardless of pri) The results reported in the paper can also be obtained by changing the pri from 0.65 to 0.81 FREQUENCY THRESHOLDS: N.Cut: Lower bound 1 Threshold 3 Upper bound 3
2016: CONSISTENCY THRESHOLDS: EPI/OSI/TEL: exclusion, crossover and inclusion fixed 0.25, 0.49 and 0.75 respectively HCI: No upper or lower bound for exclusion and inclusion, but crossover fixed at 0.49 CONSISTENCY RANGE: Raw Consistency T.: Lower bound 0.8 Threshold 0.8 Upper bound 0.88 (regardless of pri) The results reported in the paper can also be obtained by changing the pri from 0.65 to 0.82 FREQUENCY RANGE: N.Cut: Lower bound 1 Threshold 3 Upper bound 3
2018: CONSISTENCY THRESHOLDS: EPI: No upper bound for inclusion and no lower bound for exclusion, but crossover fixed at 0.49 OSI: No upper or lower bound for exclusion and inclusion, but crossover fixed at 0.49 HCI: No lower bound for exclusion, but crossover and inclusion fixed at 0.49 and 0.75 respectively TEL: No upper bound for inclusion, but exclusion and crossover fixed at 0.25 and 0.49 respectively CONSISTENCY RANGE: Raw Consistency T.: Lower bound 0.75 Threshold 0.8 Upper bound 0.92 (regardless of pri) The results reported in the paper can also be obtained by changing the pri from 0.65 to 0.85 FREQUENCY RANGE: N.Cut: Lower bound 2 Threshold 3 Upper bound 4
2020: COSISTENCY THRESHOLDS: EPI/HCI: No upper bound for inclusion and no lower bound for exclusion, but crossover fixed at 0.49 OSI: No upper or lower bound for exclusion and inclusion, but crossover fixed at 0.49 TEL: No upper bound for inclusion, but exclusion and crossover fixed at 0.25 and 0.49 respectively CONSISTENCY RANGE: Raw Consistency T.: Lower bound 0.75 Threshold 0.8 Upper bound 0.92 (regardless of pri) The results reported in the paper can also be obtained by changing the pri from 0.65 to 0.76 FREQUENCY RANGE: N.Cut: Lower bound 3 Threshold 3 Upper bound 9

Necessary conditions reported in bold below. Please note that in the paper we only focus on those necessary conditions that are consistently necessary throughout the period under investigation.

High EGDI 2003 Cons.Nec Cov.Nec RoN **c_hci 0.9977 0.3707 0.3085**	Low EGDI 2003 Cons.Nec Cov.Nec RoN **~c_osi 0.9878 0.8595 0.6163** **~c_tel 0.9902 0.8085 0.4396** **~c_epi 0.9967 0.7871 0.3453**
High EGDI 2004 Cons.Nec Cov.Nec RoN **c_hci 0.9976 0.4015 0.3250**	Low EGDI 2004 Cons. Nec. Cov. Nec. RON **~c_osi 0.9781 0.8753 0.7073** **~c_tel 0.9910 0.7791 0.3935** **~c_epi 0.9967 0.7588 0.3076**
High EGDI 2005 Cons.Nec Cov.Nec RoN **c_hci 0.9968 0.4316 0.3307**	Low EGDI 2005 Cons.Nec Cov.Nec RoN **~c_osi 0.9644 0.8822 0.7643** **~c_tel 0.9887 0.7499 0.3683** **~c_epi 0.9965 0.7360 0.3051**
High EGDI 2008 Cons.Nec Cov.Nec RoN **c_hci 1.0000 0.4681 0.2964**	Low EGDI 2008 Cons.Nec Cov.Nec RoN **~c_osi 0.9731 0.8394 0.7118** **~c_tel 0.9868 0.7173 0.3849** **~c_epi 0.9901 0.6935 0.3044**

High EGDI 2010 Cons.Nec Cov.Nec RoN **c_hci 1.0000 0.4374 0.2561**	Low EGDI 2010 Cons.Nec Cov.Nec RoN **~c_osi 0.9937 0.7750 0.5064** **~c_tel 0.9864 0.7508 0.4470** **~c_epi 0.9984 0.7231 0.3410**
High EGDI 2012 Cons.Nec Cov.Nec RoN **c_hci 0.9998 0.5942 0.3728**	Low EGDI 2012 Cons.Nec Cov.Nec RoN **~c_osi 0.9574 0.8083 0.7638** **~c_tel 0.9913 0.7090 0.5613** **~c_epi 0.9903 0.6241 0.3574**
High EGDI 2014 Cons.Nec Cov.Nec RoN **c_hci 0.999 0.602 0.461**	Low EGDI 2014 Cons.Nec Cov.Nec RoN **~c_osi 0.960 0.811 0.740** **~c_tel 0.989 0.793 0.689** **~c_epi 0.937 0.792 0.721**
High EGDI 2016 Cons.Nec Cov.Nec RoN **c_hci 0.997 0.661 0.519**	Low EGDI 2016 Cons.Nec Cov.Nec RoN **~c_osi 0.917 0.862 0.857** **~c_tel 0.994 0.755 0.661** **~c_epi 0.893 0.850 0.850**
High EGDI 2018 Cons.Nec Cov.Nec RoN **c_hci 0.996 0.748 0.554**	Low EGDI 2018 Cons.Nec Cov.Nec RoN **~c_tel 0.998 0.694 0.671**
High EGDI 2020 Cons.Nec Cov.Nec RoN **c_hci 0.993 0.811 0.589**	Low EGDI 2020 Cons.Nec Cov.Nec RoN **~c_osi 0.902 0.777 0.864** **~c_tel 0.958 0.797 0.868**

Descriptive statistics using uncalibrated conditions and outcomes:

	egdi	epi	osi	hci	tel
All countries					
Mean	0.550	0.387	0.494	0.784	0.382
Median	0.545	0.313	0.497	0.830	0.347
p25	0.404	0.091	0.295	0.714	0.141
p75	0.716	0.652	0.706	0.904	0.606
Standard deviation	0.208	0.312	0.268	0.176	0.262
Developed countries					
Mean	0.766	0.594	0.708	0.926	0.665
Median	0.781	0.627	0.721	0.937	0.682
p25	0.691	0.349	0.568	0.890	0.566
p75	0.845	0.832	0.872	0.970	0.785
Standard deviation	0.104	0.288	0.190	0.055	0.154
Developing countries					
Mean	0.477	0.317	0.422	0.736	0.287
Median	0.485	0.236	0.409	0.780	0.237
p25	0.357	0.063	0.225	0.672	0.110
p75	0.596	0.549	0.606	0.860	0.433
Standard deviation	0.183	0.288	0.251	0.177	0.219