ARTICLE IN PRESS

Government Information Quarterly xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Government Information Quarterly

journal homepage: www.elsevier.com/locate/govinf

Transparency in policy making: A complexity view

Sabine Brunswicker[a,*], Laia Pujol Priego[b], Esteve Almirall[b]

[a] Purdue University, 155 S Grant St, West Lafayette 49707, United States
[b] ESADE Business School, Universitat Ramon Llull, Av. Torre Blanca, 59, SantCugat-Barcelona, Barcelona, Spain

A B S T R A C T

The literature on transparency in participatory policy making is flourishing. With the increased digitization of our world, recent work suggests that the digitally-enabled relationships of how policy makers and citizens observe each other may transform policy making in a fundamental way. In this paper, we use complexity theory to examine how digitally-enabled transparency affects the effectiveness of policy making in aligning citizens with the policy goal to improve collective human welfare. We map Kauffman's NKC fitness landscape model, a generalizable theory of co-evolutionary complexity, to the phenomenon of transparent policy making in order to explain how transparency as an enabling generative mechanism encourages citizens to align with the policy goal without exercising central control. In our framework, citizens are agents who co-evolve by adapting to information available in their citizen landscapes. These landscapes represent the citizens' decision context, which policy makers observe and modify throughout an iterative policy cycle. In our study we identify three types of transparencies that relate to three properties of the citizens' decision context: (1) individual decision interdependence; (2) decision bias; and (3) collective decision interdependence. Using conceptual modeling, a form of inquiry combining formal representation with empirical sense making in three policy domains (e-health, smart transportation, and smart energy), we articulate and empirically validate two generative mechanisms that explain transparency effects for each of the three transparencies: (1) orchestration via iterative landscape "tuning" to reduce ambiguity and simplify citizens' alignment with the policy goal; and (2) social learning via information sharing, a co-evolutionary social "nudge" that encourages citizens to be more open to behavioral changes. Our findings have implications for the literature on transparency in participatory policy making as well as the literature on complexity in public policy and public administration.

1. Introduction

The flourishing scholarly discourse on e-government, e-participation, and platform-based governance points to the importance of digitally-enabled transparency to organize the process of public policy making in a more participatory way (Dawes & Helbig, 2010). In such participatory policy making, *digitally-enabled transparency*, or transparency for short, describes a digitally-mediated institutional relationship between policy makers and citizens during the policy-making cycle (adapted from Meijer, 2013, p. 430), in which those actors can observe each others' behaviors or/and their outcomes. Existing work examines transparency in different ways. Much of the literature discusses how transparency promotes democracy with effects on *accountability* by making final decisions of policy makers inside the governments observable to citizens (e.g., via open data portals which provide access to fiscal budgets) (Attard, Orlandi, Scerri, & Auer, 2015; Harrison & Sayogo, 2014). However, the more recent discourse takes a more integrative view and suggests that transparency can transform the whole cycle of policy making, from problem definition to evaluation of policy solutions, in a more fundamental way (Eppel Rhodes, 2012; Matheus, Janssen, & Maheshwari, 2018). In essence, transparency as an integral element of policy making may offer new opportunities to increase the *effectiveness* of policy making, broadly defined as the alignment of civic behaviors with the goal of public policy making to produce socially desirable outcomes, or in short, greater collective human welfare (Shafir, 2013, p.1).

The emergence of such an *integrative view* has been caused by technological advances "whereby boundaries between the government and the public fade" (Linders, 2012). "Government as a platform" (Linders, 2012) makes increasing use of technologies like social media, the Internet of Things (IoT), and data analytics. These technologies establish citizens as active producers and users of policy-related information, and allow policy makers to collect, aggregate, and interpret large amount of information about their citizens' behavior throughout the policy cycle (Janssen & Kuk, 2016). Having such transparency about their citizens' behavior offers policy makers new and more indirect roles as "orchestrators" of the discovery and evaluation of policy solutions (Janssen & Helbig, 2016). Furthermore, policy makers may utilize and share their insights about civic behavior with the public to create indirect *levers* for policy making, which do not restrict citizens' freedom of choice (Janssen & Helbig, 2016; Linders, 2012). For example, sharing social information with the citizens may *nudge* them to align with the policy goal because such information encourages them to become socially aware (Sunstein, 2014). In sum, the focus has shifted

* Corresponding author.
E-mail addresses: sbrunswi@purdue.edu (S. Brunswicker), laia.pujol@esade.edu (L. Pujol Priego).

https://doi.org/10.1016/j.giq.2019.05.005
Received 21 February 2018; Received in revised form 3 March 2019; Accepted 19 May 2019
0740-624X/

Please cite this article as: Sabine Brunswicker, Laia Pujol Priego and Esteve Almirall, Government Information Quarterly, https://doi.org/10.1016/j.giq.2019.05.005

from asking what makes policy making transparent to the question of how to utilize transparency as an enabling mechanism for effective policy making.

Building upon Janssen and Helbig (2016), we argue that such an integrative view is at odds with a rational-technical view towards policy making (e.g., Misuraca, Codagnone, & Rossel, 2013), relying on sequential expert-driven processes and formal "mechanistic" policy analysis (Brewer & DeLeon, 1983) guided by policy models (e.g., Hurwicz, 1973) that assume that policy making can optimally solve policy problems. Such an approach fails to account for the *complexity* that is inherent to policy making (Janssen & Helbig, 2016; Janssen & Kuk, 2016; Noveck, 2015). A complexity view suggests that policy making is concerned with a complex adaptive system (CAS) of diverse citizens, or in short, a civic CAS, which is never in an equilibrium but depicts a constantly *evolving* structure (Holland, 1992; McKelvey, 1999). Evolutionary structure illustrates that CAS's agents – the citizens – constantly adapt to information available in their unique surroundings, their local decision environment, in a self-organizing way (Holland, 1992, p.18). This local decision environment consists of multiple interrelated decision attributes. Policy makers shape this environment throughout the overall policy cycle. As a result, transparency as an integral part of policy making shapes how citizens adapt in response to information in their local environment. What is important though, is that evolutionary structures that emerge from such "local" adaptation in response to transparency in policy making may cause nonlinear and potentially harmful dynamics at the collective level that can neither be predicted nor optimized. On the contrary, complexity theory with its origin in biology suggests that a civic CAS requires "*generative mechanisms*" (Kauffman, 1993; McKelvey, 1999), system immanent properties that equip the civic CAS with a capacity to generatively evolve towards greater collective human welfare. Such generative mechanisms are distinct from economic incentive-oriented mechanisms (e.g., Maskin, 2008), which lack the consideration of evolutionary structures emerging from local adaptation. Thus, returning back to the role of transparency for *effective* policy making, the question to be asked is: *What are the generative mechanisms that explain how transparency in policy making enables a civic CAS to evolve towards greater human welfare?*

By answering this question, we respond to the recent call of scholars in the field of public policy and public administration (Eppel & Rhodes, 2018; Gerrits & Marks, 2012) to turn to complexity theory when studying policy making, and to consider the framework of a complex adaptive system (CAS) (Holland, 1992; Kauffman, 1993; McKelvey, 1999) and one of its fundamental concepts of a fitness landscape (see Section 2.2) (Kauffman, 1993; Rhodes, 2008). Both have their origin in biology and physics but have been adapted to social sciences and, in particular, to organization science (Anderson, 1999; Levinthal & March, 1981; McKelvey, 1999). In a policy making context, a fitness landscape offers a new way to conceptualize the citizens' decision environment that policy makers shape with their actions (Rhodes, 2008, p.362) as civic fitness landscapes on which citizens – the agents – adapt in response to information about their landscapes. We introduce transparency in policy making as a theoretical property that affects this landscape. Specifically, we extend the NKC fitness landscape model (Kauffman, 1993, 1995), an extension of Kauffman's (1993) NK fitness landscape model (see Section 2.2.2). The latter has been translated into social sciences, including public policy and public administration (Eppel & Rhodes, 2018). The NKC fitness landscape offers a general theory to articulate the generative sources of complexity that cause citizens to adapt on their citizen landscapes.

Our method of inquiry for theory development on transparency in policy making triangulates between formal representation of the key properties of the NKC fitness landscape model and empirical sense making through retrospective analyses of instrumental cases and secondary literature (Stake, 1995), also referred to as *conceptual modeling* in the CAS literature on public policy (Rhodes & Dowling, 2018 p. 1002). We apply the NKC fitness landscape model as a theoretical apparatus "to analyze empirical puzzles and their theoretical representations" (Marks, Gerrits, & Marx, 2019 p.7). We choose empirical settings in e-health, smart transportation, and smart energy, in which policy makers practice transparency in policy making. We use these empirical data to complement the process of formal representation of the key properties of the NKC fitness landscape model. Further, our empirical analysis allows us to empirically reflect upon the two generative mechanisms that explain how transparency affects the effectiveness of policy making: (1) *Orchestration* via *citizen landscape tuning* describing policy makers' new roles as "orchestrators" who utilize transparency to tune citizen landscapes into smooth ones that reduce ambiguity and uncertainty for the citizens (Janssen & Helbig, 2016); and (2) *social learning* via *information sharing* that shifts a citizen's attention to other more unfamiliar choices and increases tolerance to unfamiliar and more uncertain choices (Linders, 2012; Shafir, 2013; Sunstein, 2014). Both explain how transparency can create conditions that lead to generative co-evolutionary adaptation, *adaptation* for short, of a civic CAS. Our findings contribute to two streams of literature in public policy, namely: (1) digitally-enabled transparency in participatory policy making; and (2) complexity in public policy.

In the next section, we briefly review these two streams of literature. In Section 3, we discuss our method and provide background on the three instrumental cases. Section 4 presents the results of our study: We first translate the NKC model into the context of transparent policy making; we model the tri-partite view on transparency and we explain its impact on policy making success via two types of generative mechanisms. Afterwards, we summarize our implications for the two streams of literature related to our study, and conclude with future developments of a new complexity-oriented view of transparent policy making.

2. Background and related work

There are two broad streams of literature of relevance for our research question, one concerned with the role of digitally-enabled transparency in participatory policy making, and the second with complexity in public policy and public administration. We will next position our paper within those two streams and clarify how it builds upon those topics.

2.1. Digitally-enabled transparency in participatory policy making

Existing literature has tackled the concept of transparency from different theoretical lenses and with different research methods, spanning conceptual work, case studies (e.g., Rhodes, 2012), and quantitative studies at regional, national, and international scales (e.g., Bertot, Jaeger, & Grimes, 2010; Jaeger & Bertot, 2010).

A review of existing work reveals that transparency is discussed across various research streams with a strong focus on ICT, such as e-government, e-participation, e-democracy, policy making 2.0, and data-driven policy design. As defined in the introduction, transparency is an institutional relationship between policy makers and citizens (Meijer, 2013) and their ability to observe each other's behaviors and/or their outcomes. More specifically, transparency can be characterized in terms of: (1) the subject (who is observing) – object (who is observed) relationship; (2) the impact or effects of such transparency; and (3) the research focus of such transparency related to what is transparent (input, output, and performance) and how it is made transparent (processes, actions, decisions, opinions, and so forth). We classify the existing three views, which vary in terms of how deeply and broadly transparency is viewed along these three dimensions (Table 1).

First, important transparency research relates to questions on how to realize *access* to governmental information for citizens to spur democracy and accountability (*access view* in Table 1) (e.g. Dawes, 2010; Dawes & Helbig, 2010; Harrison & Sayogo, 2014). Extensive studies at a global scale have indicated that access can foster democracy and battle

Table 1
Classification of transparency in policy making.

Transparency view	Object-subject relationships	Transparency impact	Research topics	References
Access/data view	• Citizen is subject and has transparency about governmental data • "Policy maker" is object and discloses data	• Accountability • Democracy • Anticorruption • Trust	• Open data • Anticorruption policies • *E*-services • E-voting	e.g., Attard et al. (2015); Harrison and Sayogo (2014); Jaeger and Bertot (2010)
Dialogue View	• Citizen is primarily subject and engaging in dialogue with policy maker; partially also object when sharing opinion • Policy maker is object and shares information openly; partially also subject by listening	• Engagement • Sourcing external knowledge • Active participation of citizens in policy making	• E-participation • Civic participation • E-government	e.g., Bertot et al. (2010); Medaglia, 2012; Nam, 2012); Sæbø, Rose, and Skiftenes Flak (2008); Susha and Grönlund (2012)
Integrative View	• Citizen is object of transparency given a civic-centric view towards transparency • Both, policy maker and citizens are subject as well as beneficiary of 'transparency' of behaviors related to a particular policy goal, transparency-enabled nudging citizens into socially desirable behavioral goal	• Effectiveness of policy making • New roles (and skills) for policy makers • Nudging and indirect levers for behavioral change	• Government as a platform • Policy making 2.0 • Nudging and information sharing • Algorithmic policy making	e.g., Dunleavy, Margetts, Bastow, and Tinkler (2006); Janssen and Helbig (2016); Janssen and Kuk (2016); Lathrop and Ruma (2010); Linders, 2012; Matheus et al. (2018); Meijer (2013)

corruption by making the outcomes of decisions, rules, and other critical data inside governments accessible to external citizens (e.g., Bertot et al., 2010; Harrison & Sayogo, 2014; Jaeger & Bertot, 2010). In such discussions, scholars highlight ICT challenges (including data quality, provenance, data standards, machine readability, etc.) and call for a more sustainable long-term view towards transparency (Jaeger & Bertot, 2010). Second, and complementary to the *access view*, scholars have pointed to the role of transparency in civic participation and new ways to strengthen the relationship and *dialogue* between policy makers and citizens (e.g. Medaglia, 2012). In this *dialogue view*, scholars have highlighted the opportunities but also the challenges (e.g., technological barriers or lack of incentives) in using digital technologies for participatory policy making to facilitate the dialogue between policy makers and citizens beyond traditional participation through electoral voting (Rojas, 2014). A key measure of success for transparency is the quantity and quality of civic participation.

Third, and more recently, transparency has been discussed in a more *integrative way*. In an integrative view, the object-subject relationship of transparency shifts from a primary focus on the observability of choices inside the government to granular insights about citizens' choices and behaviors related to policy makers' goals and actions (civic-centric). Under this approach, digital technologies enable "governments to act as platforms" (Linders, 2012, p. 447) to collect, aggregate, interpret, and also disseminate rich behavioral insights about citizens who are active producers but also users of policy-related information. Scholars point out that an integrative view requires policy makers to take more "neutral and independent roles" (Janssen & Helbig, 2016 p. 6). Existing literature suggests that transparency allows policy makers to take such roles in two ways. First, such transparency becomes important for the recent uptake of more iterative policy-making processes in which policy makers act as orchestrators that iteratively design, test, and evaluate a greater variety of policy solutions. Orchestration implies that policy makers take a more indirect role during these iterative policy-making cycles (Janssen & Estevez, 2013; Janssen & Helbig, 2016). Instead of providing solutions, they need to focus their capabilities on "discovering solutions and monitoring the effect of policy implementation" (Janssen & Helbig, 2016, p.6). Further, policy makers as orchestrators are able to optimize human welfare but instead supervise this process with a focus on the consistency of data (and their refinement into algorithms) and related policy solutions in order to observe whether and how they drive behavioral change (Janssen & Kuk, 2016).

Second, transparency affords policy makers to realize *behavioral levers* that "nudge" citizens into socially desirable behavior (European Comission, 2019; Profir, 2015; Shafir, 2013; Sunstein, 2014). Informed by insights from behavioral sciences (e.g., psychology and behavioral economics) (Gigerenzer & Todd, 1999; Sunstein, 2014; A. Tversky & Kahneman, 1986), policy makers purposively share behavioral data in order to subtly encourage behavioral change without restricting freedom of choice (e.g. Linders, 2012). For example, data-driven policy solutions, such as dashboards reporting energy consumption data of a particular housing community (Janssen & Helbig, 2016; Janssen & Kuk, 2016; Linders, 2012; Thaler & Sunsteing, 2009), may encourage residents to adjust their behavior to social norms emphasizing what "most others are doing" (Sunstein, 2014 p. 586). Just like a fitness app that tells individuals, on average, how many miles most bikers ride, do such nudges tap into the fact that humans' decision making incorporates social information available (Gigerenzer & Todd, 1999; Simon, 1955), like "follow what most others are doing." Thus, instead of using direct forms of policy interventions (such as taxes), transparency affords new, inexpensive, and more self-organizing mechanisms for aligning citizens with policy goals.

We will next review the literature on complexity in public policy and public administration.

2.2. Complexity theory and policy making

Over the last decade, governmental officials and policy makers have recognized that policy practice increasingly relates to complex systems "that are prone to surprisingly, large-scale, seemingly uncontrollable behavior" (Rhodes & Dowling, 2018, p. 997), rending traditional models and tools used for policy making inappropriate. Somewhat in parallel, scholars have turned to theories of complexity to develop new theories and guide empirical research in the field of public policy and public administration (Schneider, 2012). This stream of research emerged in opposition to a rational, linear, and realism-oriented view. While there are several frameworks and theoretical perspectives towards complexity in policy making[1] (e.g. Head & Alford, 2015; Schneider Rhodes, 2012), our review of this literature focuses on those contributions that relate to studies following a framework of CAS and utilizing fitness landscape models (Gerrits & Marks, 2014) to represent them visually or formally (Gerrits & Marks, 2012; Teisman & Klijn, 2008). We will introduce both concepts, given their relevance for this paper. Then, we will discuss how prior literature in public policy and public management has embraced them.

2.2.1. Key properties of complex adaptive systems (CAS)

A *complex adaptive system (CAS),* composed of heterogenous agents, is defined as a system that adapts in the process of interacting with its environment in a nonlinear and dynamical way (Gell-Mann, 1995; Holland, 1992). CAS can be biological (e.g., such as the immune system), technical (e.g., power grids), social (e.g., organizations or citizen communities). *Self-organization* and *adaptation* are two essential CAS properties which scholars in policy and public administration have emphasized (e.g., Klijn, 2008; Rhodes, 2008).

Self-organization is the property of the system to spontaneously *generate* new structures. This *generative* aspect is *not* the result of a priori design, but it surfaces from the interaction of the autonomous agents with the information in their local environment as well as the local direct and indirect interactions between the agents (Gell-Mann, 1995). *Adaptation,* also called *evolutionary adaptation* (Kauffman, 1993), describes how this generative capacity is caused by the local self-organizing processes: Agents adapt in response to information in their environment because they want to achieve greater "fitness" (Kauffman, 1993; Wright, 1932). Originally in biology, the Darwinian "fitness" of biological trait describes how successfully an organism with that trait can pass on its genes (Rhodes & Dowling, 2018 p. 998). The key idea of adaptation is that the agents' behavior is dynamic because they try to achieve higher fitness and thus they engage in trial-and-error search processes in response to *information feedback* from the environment (Kauffman, 1993, 1995).

Fitness landscape models have been developed to formally represent this process of evolutionary adaptation. They offer a general theory that articulates the *sources of complexity* causing evolutionary adaptation in any kind of a CAS, including social ones (Kauffman, 1993; Kauffman & Levin, 1987; Levinthal & Warglien, 1999; McKelvey, 1999). Further, these models also offer a way to represent transparent policy making as a property of the landscape, which defines what is visible for the agents that adapt on the landscape, as well as for the originator of the CAS. We will next introduce the NK fitness model, with the NKC model being a particular form of it.

[1] For example, the ideas of complexity, dependency, unpredictability, and connectivity, also at the core of complex decision-making theories and models such as the mutual partisan adjustment (Lindblom (e.g., Lindblom, Lindblom & Cohen, 1979) and model II (a partisan model) in the multiple perspective approach of (Allison, 1971). However, they are not concerned with evolutionary adaptation.

2.2.2. Key properties of NKC fitness landscape models

The NK landscape model, and its refined version of NKC, was developed by Kauffman (1993) in response to original ideas and mathematical modeling presented by Wright (1932), as a model to represent and simulate CAS in evolutionary biology. However, the generality of Kauffman's NK models, and its ability to allow for a description of other complex systems, triggered follow-up research in other fields. In social science, it was Levinthal (1997) who translated the model to an organizational context in order to represent organizational adaptation on *rugged fitness* landscapes (Levinthal, 1997).This seminal work inspired a range of other studies concerned with social systems or sociotechnical systems in the field of economics, organizational and management science, and innovation studies (Koput, 1997, Anderson, 1999, McKelvey, 1999, Levitan, Lobo, Schuler & Kauffman, 2002, Davis, Eisenhardt, & Bingham, 2007, Lin, Kitts, Yang, & Harrison, 2008, Davis, Eisenhardt, & Bingham, 2009, Almirall and Casadesus-Masanell, 2010, Tracy et al., 2013).[2] In these disciplines, it has also been used to represent technical systems (e.g., Frenken, 2006). Further, it has also been translated into other fields of sciences such as evolutionary psychology (Rellihan, 2012), and recently also to the interdisciplinary field of information systems, if relevant to readers of these papers (Brunswicker, Almirall, & Majchrzak, 2019).

Kauffman's (1993) NK fitness landscape model is a theoretical model of complex evolutionary adaptation that was originally developed as an alternative explanation for Darwin's selection theory in evolutionary biology, "by suggesting that under some circumstances complexity may intervene to offer alternative bases of biological order" (McKelvey, 1999, p.301). In its original version, the model maps an organism's "attributes" to its fitness level (Kauffman, 1993).[3] "In a biological system, these attributes may represent genes, while in a social system such attributes may be particularly organizational or governance decision factors (e.g., competence). Following seminal translation of Levinthal (1997), and key follow-up work including his own (Levinthal & Warglien, 1999) and those of McKelvey (1999), there are two fundamental properties of the NKC fitness landscape model as a means to represent evolutionary adaptation: (1) *rugged fitness landscapes* with internal interdependence; and (2) heterogenous, behaviorally *bounded agents* as "searchers" of multiple landscapes with external interdependence. Table 2 describes those two properties.

1. Rugged fitness landscape: An NKC fitness landscape represents a "decision space" with all potential alternatives for combining different states of *N* different decision factors (the axis) in an *N* dimensional space. *N* defines the size of the landscape. Each combination of different decision factors is mapped into a fitness value ($N + 1$ dimension), where fitness describes the potentially achievable performance value associated with a particular combination. Visually speaking, there are different locations. Variability in fitness values creates valleys and peaks in the performance surface, which define the ruggedness of the landscape's surface or, visually speaking, the number of peaks. *K* describes the interdependencies between the *N* decision factors. Essentially, they make the landscape look more or less rugged or jagged, in the sense that different locations and the fitness value mapped onto them may have very similar or very dissimilar "heights." *K* as a property of the landscape is a source of complexity (McKelvey, 1999), which we will discuss in greater depth later (Section 4).

[2] Complexity science and simulations are overcoming the difficulty and limitations of empirical studies and experiments to cover all relevant variables and events.

[3] It is worth pointing out that Kauffman (1993) originally used two kinds of models, one from statistical physics and one from cellular automata originating in electronic computer design, which are not originating from biology (Lindblom, Lindblom & Cohen, 1979)

Table 2
Key properties of co-evolutionary NKC fitness landscape models.

Key NKC fitness landscape properties	Description of key properties and attributes	Primary sources of dynamic complexity and co-evolutionary adaptation
Multiple rugged landscapes	• A fitness landscape represents a decision space with all potential alternatives for combining different states of *N* different decision attributes (the axis) in an *N* dimensional space. • Each combination of *N* decision attributes represents a location in the landscape that is mapped onto a fitness value. The landscape has valleys and peaks. • The factor *K* describes the ruggedness of an individual landscape	Internal dependencies *K* between decision attributes
Agents as behaviorally bounded searchers of multiple landscapes	• Agents are adaptive searchers who search a landscape to achieve a higher fitness. • As boundedly rational agents, they are guided by simple search heuristics when interpreting information observable about the NKC landscapes • Agents satisfice and prefer to search locally using hill-climbing before considering other more uncertain options • Agents are not autonomous but mutually influence each other when searching their idiosyncratic landscapes.	• Decision biases inherent to search heuristics • External dependencies *C* between different agents and their landscapes

The factor C is related both to the landscape as well as the agent behavior and thus we have not assigned it to one aspect only. However, given the importance of the dynamics in co-evolutionary adaptation, we later establish co-evolutionary linkages as a separate source of complexity that requires specific attention.

2. Agents as behaviorally bounded "searchers" of landscapes: In the NKC model, agents are the searchers that traverse one (or several) landscapes, making a series of discrete search moves, each presenting a decision in a stylized way. They move from one location to the next in order to improve their fitness. Building upon prior NK modeling in organizational science, agents in their role as searchers are assumed to be boundedly rational (Kauffman, 1993) because of cognitive processing limitations: They lack the perfect rationality of a hypothetical agent who has complete information about the options available for a choice and who has perfect foresight of the implications of all potential choices (Simon, 1955). Neither do they know (or "see") all locations in the landscape, nor the height of their peaks (Kauffman, 1993; Levinthal, 1997). Instead, agents typically only perceive and judge choices that are very similar to their current ones, or, in other words, they can only see and interpret (or judge) information about neighboring locations in their landscapes, including their fitness. Thus, agents as fitness landscape searchers with bounded rationality typically aim to exploit opportunities for fitness improvement nearby through *local* search, a search move that Kauffman (1993) originally referred to as *hill-climbing* (Kauffman, 1993; Levinthal & March, 1981; Levinthal & Warglien, 1999; McKelvey, 1999). If such *local search* bears fitness benefits (a higher peak), they move there without considering further locations. Only if they have access to additional information about the landscape might they take a *distant search* move, also called a *long-jump* to a distant "uncertain" location they cannot assess well. The distinction between *local* versus *distant* (or hill-climbing versus long-jump) mirrors the well-known distinction of *exploitation-exploration*, used across various disciplines concerned with evolutionary search and adaptation, from space, mind, and society (Hills, Todd, Lazer, Redish, & Couzin, 2015). In some cases, bounded rationality might lead to incorrect perceptions of the fitness associated with the new location, in the sense of a *decision bias* that deviates from the fitness hypothetically achievable with that option (Rellihan, 2012; Amos Tversky & Kahneman, 1974). However, bounded rationality should not always be equaled with "irrationality" since, in many cases, simple search heuristics make people "smart" (Gigerenzer & Todd, 1999; Simon, 1973): They do the best they can to perceive and interpret information available to them, which allows them to make choices efficiently.

Further, the NKC model, an extension of the NK model, also accounts for the fact that the agents, despite their autonomy, are also interdependent when searching their landscapes. In other words, if one agent searches on her/his landscape, such a move affects the surface of other agents' landscapes. In the NKC model, such external links between different landscapes are represented with the factor *C* (Kauffman, 1993; Levinthal & Warglien, 1999; McKelvey, 1999).

Both the nature of: (1) an agent's search heuristics and, in particular, potential *decision bias* inherent to them, and (2) the external links *C* among different landscapes are a source of complexity that may lead to unexpected, nonlinear adaptation. We will discuss both in greater depth in later sections.

After introducing the key properties of co-evolutionary CAS and the NKC fitness model, we will next review related literature in public policy and public administration (Gerrits & Marks, 2014; Rhodes & Dowling, 2018; Teisman & Klijn, 2008).

2.2.3. CAS and NKC fitness landscape model in public policy and public administration

The literature on co-evolutionary complexity in public policy and public administration has used and translated both the CAS framework (e.g., Teisman & Klijn, 2008) as well as the concept of a NK fitness landscape (e.g.,Gerrits & Marks, 2014; Rhodes & Dowling, 2018) to the context of public policy and public administration. Extending (but without repeating) recent literature reviews (Gerrits & Marks, 2014; Rhodes & Dowling, 2018), we discuss (1) the nature of inquiry; (2) the focus in policy cycle; (3) the nature and scope of representing co-evolutionary adaptation on NK fitness landscapes; and (4) the consideration of transparency as a key construct in theory development based on fitness landscapes.

Nature of Inquiry: Scholars in public policy and public management use either a metaphorical (and sensitizing) method of inquiry focused on illustrative and conceptual cues of a visually imagined rugged landscape, or on what Rhodes and Dowling (2018) call a "modeling" method of inquiry. The latter engages more deeply with the key attributes of the family of NK fitness models, introduced in the prior section. Such an inquiry implies a more detailed process of theoretical description and causal sense making,[4] typically through empirical analysis of historical and retrospective data. In this paper, we pursue such a form of sense making-oriented modeling with a purposive selection of three instrumental cases.

The focus in policy cycle: In terms of focus across the policy cycle, existing inquiry is either focused on policy analysis (and design) (e.g., Geyer & Pickering, 2011), or on policy implementation (e.g., Butler & Allen, 2008), or in rare cases both (e.g., Gerrits & Marks, 2012; Schneider Rhodes, 2012). Further, it is worth noting that

[4] This definition of modeling does not imply simulation-based theory development, as performed by Levinthal (1997) or other scholars (e.g., Rivkin & Siggelkow, 2007).

fitness landscape has been used in very different policy areas, ranging from anticorruption programs (Michael, 2004), ICT and education programs (Toh & So, 2011), environmental education programs (Astbury, Huddart, & Théoret, 2009), or protesters' behavior against public policies (Sword, 2007). Such studies look primarily into the search decisions of policy makers, those developing the policies, instead of focusing on citizen landscapes, searched by citizens.

The nature and scope of representing co-evolutionary adaptation: Policy scholars either metaphorically engage or formally model the key properties of co-evolutionary complexity of NKC, namely: (1) landscape (e.g., NK fitness); and (2) the agents and their adaptive search processes. With respect to: (1) Rhodes and Dowling (2018), they note in their literature review that NK fitness landscape models translated into the context of public policy and public administration often fail to properly specify the key properties of the landscape such as fitness or internal interdependencies (K). With respect to (2) scholars, they represent variability in terms of local (or hill-climbing) versus distant (or long-jump) search moves (e.g., Astbury et al., 2009). Despite such attempts to engage with the model, we learn that there is little effort to disentangle different kinds of sources of complexity. Further, many studies insufficiently account for the "relationships among agents and their effect on the choices made and the level of fitness achieved" (Rhodes & Dowling, 2018, p. 1000). Even though some policy scholars focus their inquiry on actor relationships in a CAS (Klijn, 2008), such attempts do not recognize the importance of indirect (rather than direct) co-evolutionary relationships that are distinct from social network and communicative ties. In this paper, we address those gaps and disentangle different sources of complexity, and also represent two distinct interdependencies (within and across landscapes).

Transparency: Even though scholars have realized the importance of information dissemination among the different agents (Gerrits & Marks, 2014; Rhodes & Dowling, 2018), the existing discourse lacks a granular conceptualization of transparency as a property of the fitness landscapes (N, K, C) as well as their searchers (the agents). Furthermore, the generative relationships between transparency and co-evolutionary adaptation are not sufficiently explored. Against this background, we will next introduce the method of inquiry that we use to build upon and extend existing literature on CAS and NK fitness landscape models in public policy and public administration.

3. Method

3.1. Research design

In this paper, our goal is to close the gap in the literature on transparency as well as complexity in public policy and public administration. To do so, we develop a theoretically- and empirically-grounded explanation of the *generative mechanisms* allowing *transparency* to afford effective policy making. To do so, we follow related studies in the public policy and public administration (Eppel, 2012; Gerrits & Marks, 2012; Rhodes & Dowling, 2018) and organizational and administrative sciences (Afuah & Tucci, 2012; Levinthal & Warglien, 1999). We adopt what Rhodes and Dowling (2018) call conceptual modeling to study the role of transparency in a civic CAS; for this, we used a "social" NK fitness landscape model to represent a social CAS, in which social and not biological agents adapt to their landscapes (see Section 3.2).

Following this form of inquiry, we triangulate between representation of the NKC fitness landscape model and empirical reflection through historical and retrospective case study analyses. We did this by engaging in an iterative induction and deduction process (Bergmann, 1957) that went through three major research phases over a period of four years, starting in 2013 (see Fig. 1).

First, in Years 1 and 2, we engaged in participatory observations and discussions at least two times a year by attending forums with policy makers at the regional, national, and international levels. During this phase, we also reviewed literature on transparency and identified insufficient considerations of the complexity of citizens' contexts. We identified the NKC fitness landscape model – a co-evolutionary model of complex search and decision making – as a theoretical concept for new theory development in public policy (Kauffman, 1993; Levinthal & Warglien, 1999). An initial framework to describe digital transparency from a complexity point of view was the outcome of this first phase.

Second, in Phase 2 (Years 2 and 3), we investigated secondary case data in order to refine the theory further through a method of inquiry that falls into conceptual modeling (Rhodes & Dowling, 2018). Given the novelty of the work on digital transparency, sampling of the empirical settings was performed purposively based on discussions with experts, grey literature, policy reports, and project reports. We first sampled roughly 100 potential empirical cases using three simple selection criteria: (1) digital transparency used; (2) the significance at least one of the sources of complexity (see Section 2) in a CAS; and (3) a successful outcome (evidence of some degree of behavioral change among citizens in alignment with policy goals). We considered 11 cases (see Supplement, Table A) as meeting these criteria. From the preliminary list we selected three case studies for the following reasons, comprehensively explained in Section 3.2 (p.19).

Third, in Phase 3, we iterated the modeling exercise and theoretical description of NKC in policy making with the three empirical settings to refine the framework, and most importantly, theoretically represent and empirically validate the identified generative mechanisms.

3.2. Inquiry through conceptual modeling

As stated earlier, we use *conceptual modeling* to map the NKC fitness landscape model onto the context of transparent policy making. Conceptual modeling implies a detailed theoretical description and a causal sense making[5] process combining formal representation of the model and reflection using empirical data. Originators of theories of CAS and NK fitness landscape models in social sciences (such as Holland & Miller, 1991 or Levinthal & Warglien, 1999), refer to this form of inquiry as *linguistic modeling*, and clearly distinguish it from computational simulation studies. Conceptual modeling as a form of inquiry typically builds upon prior generalizable theoretical arguments (including the original ones from Kauffman (1993)) to translate the fundamental causal arguments inherent to the NKC model and to explain a new phenomenon, such as transparency in policy making. In addition, such *theoretical representation* is typically accompanied with *empirical reflection* to advance reasoning and sense making. Through conceptual modeling, we engaged with the key attributes of the family of NK fitness models and even though we did not actually specify a complete simulation study, we completed prior theoretical claims with explorative visualizations of NKC landscape computations of different N and K values (see Figs. 3 and 4). After translating the fundamental assumptions of NKC to the transparency in civic CAS, we used empirical insights from historical and retrospective cases to make sense of the generative mechanism of transparency of civic NKC fitness landscape.

We selected three *instrumental cases* for the part of empirical reflection in our conceptual modeling in order to extend prior generalizable theoretical arguments (made by influential authors such as Levinthal and Warglien (1999)) to our new phenomenon. Instrumental cases are purposefully selected to provide insight into a particular issue (Stake, 1995). Indeed, prior generalizable arguments were an important starting point for our case selection and helped us to identify the

[5] This definition of modeling does not imply simulation-based theory development, as performed by Levinthal (1997) or other scholars (e.g., Rivkin & Siggelkow, 2007).

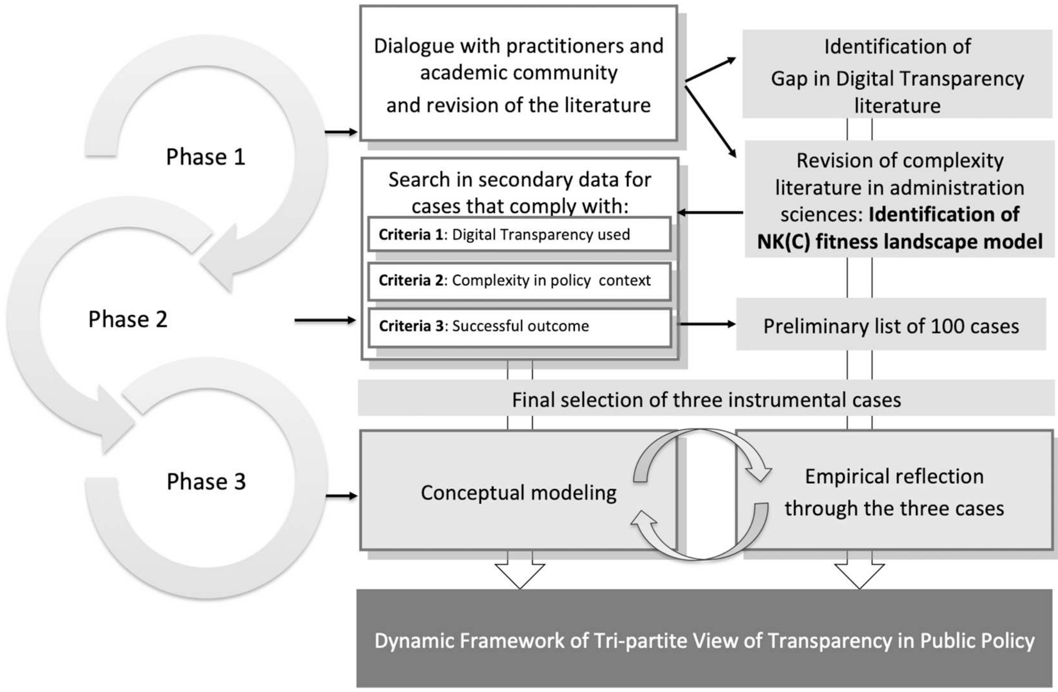

Fig. 1. Overview research process and sampling strategy.

sources of complexity as a particular issue to be examined further. Based on prior work and our empirical reflection in Phase 1 we had learned that we needed to disentangle the three different sources of complexity (which we will discuss later in Section 4). We sampled three particular historical and retrospective empirical settings that uncover transparency effects for three *different sources* of complexities of citizens' context. Each case is instrumental to understand each source of complexity and reason about the transparency effects for a particular source of complexity: Case 1 for internal dependence in landscapes; Case 2 for decision bias; and Case 3 for external interdependence between agents. Each case sheds light on the generative mechanisms that explain how transparency impacts citizens when a particular source of complexity is a key risk for effective policy making. While all three sources of complexity were present in all three case studies, we selected a case based on the source that was most pertinent for the policy goal of the case.

3.3. Data and empirical background

Before presenting our results, we provide a brief description of the three empirical settings (see Supplement for more details).

Case 1. E-Health Program in Verbano-Cusioi-Ossola (VCO)

Piedmont's regional government in Italy was facing an expenditure of around 80% of its total budget on health services (Ferro, Loukis, Charalabidis, & Osella, 2013). In order to effectively achieve a significant expenditure reduction, the Italian province of Verbano-Cusioi-Ossola (VCO) agreed in 2008, to launch an experimental eHealth pilot program that integrated a set of policy solutions in order to test an innovative approach to providing healthcare services to the population before a potential deployment to the Piedmont region.

The pilot was considered to be *successful*. The e-health policy led to: (1) an increase in positive evaluation of more than 11,000 citizens participating on the governmental platform (see Section 6.1.2 and Appendix); (2) a decrease of 63.68% in the use of emergency services; and (3) a reduction of hospital admissions by 56.25% (Ferro et al., 2013; Nunes, 2013).

The *policy solutions* that VCO developed and evaluated comprised an innovative eHealth program integrating a computerized system with a personalized service delivery. First, a technical infrastructure supported remote *monitoring* of patients in their homes for *prevention* (e.g., metrics like blood sugar level, blood pressure, etc.) because the e-health system allowed for out-of-range clinical data to be sent by the patient. Second, this monitoring was integrated into a decentralized, connected network of health providers offering different kinds of *treatment* services (e.g., who accessed the centrally-stored health records). When the monitoring detected out-of-range clinical data, the providers were automatically informed. Third, each citizen also received a personalized *diagnosis* and *referral* service across those different healthcare providers. This e-health system was integrated with a social media platform, “Padgets,” that supported an iterative policy cycle from policy analysis through monitoring and evaluation (Spiliotopoulou & Charalabidis, 2016). This platform allowed VCO to mine and analyze perceptual, communicative, and behavioral data throughout the overall policy cycle. Data analytics provided policy makers with insights into the citizens' decision architecture as well as decision patterns.

Case 2. Stockholm Congestion Charge Program

In 2006, the Stockholm municipality set a policy goal to decrease congestion in the city. With this goal in mind, policy makers in Stockholm developed, implemented, and evaluated a multidimensional *policy solution*. At the core was a congestion charging system with a toll cordon around the inner city that sought to reduce the traffic through the main bottlenecks. The system also integrated IoT to share in real time individuals' information (e.g., transportation costs). Further, policy makers also used social media to communicate publicly with citizens (Börjesson, Eliasson, Hugosson, & Brundell-Freij, 2012). The charging system modified the citizens' choice attributes in various ways. For example, it affected the *time of travel* as the amount of the charge varied between 10 and 20 SEK for different time windows during the day. It was highest during peak times. It also affected the *mode* of traveling, as it applied only to cars, while other modes were exempted (e.g., bus, bicycle, and alternative-fueled cars) (Eliasson, 2008, 2014; Karlström & Franklin, 2009). It also changed the communication of transportation changes from delayed to real time. Finally, it affected citizens' ability to be aware of environmental concerns, as policy makers used social media to widely communicate information about the social and environmental implications of the charges (Eliasson, 2008, p.22).

The pilot was considered a *success*. It resulted not only in a positive attitude towards the charge (the public support increased dramatically after the trial and remained consistently high, at roughly 70%, thereafter). But there was also a significant increase in human welfare through shorter and more reliable travel times, lower emission, and greater travel safety (Börjesson, Eliasson, Hugosson, & Brundell-Freij, 2012; Karlström & Franklin, 2009). Overall, traffic decreased by about 20% across the toll cordon, or the equivalent of 100,000 passages each day during the trial. The traffic decrease led to congestion reductions between 30% and 50% on the arterials; inner-city emission decreases between 10% and 14%; and a significant decrease in travel time variability (Jonas Eliasson, 2008, 2009, 2014).

Case 3. Kansas City Smart Grid Program

On October 18, 2010, the U.S. Department of Energy (DOE) and its partner Kansas City Power & Light (KCP&L) developed a fully integrated Smart Grid Demonstration project with a cost $48 million in an economically challenged area of Kansas City (Hedges, 2015). This pilot serviced over 14,000 consumers and was considered the first step in potential deployment in a set of municipalities (Vojdani, 2008). The team engaged in an iterative process to develop a combination of *policy solutions*, which modified the decision architecture of the citizens targeted by the policy: (1) A smart metering infrastructure included in IoT devices inside citizens' homes and meter data management services (Allen, 2011). For example, the MySmart display offers real-time and disaggregated feedback about energy consumption (heating & cooling, lighting). (2) A smart consumption component that involved real-time smart feedback features including dynamic pricing (Vojdani, 2008). Real-time feedback, displayed on smart IoT devices, made citizens aware of how electricity costs vary at different times of the day and across seasons. (3) A distributed *smart generation* component, managed through a *smartSubstation*. Citizens were able to act as producers and users of energy at different times with different prices (Wakefield & Hedges, 2010). For instance, plug-in hybrid electric vehicles could be scheduled and charged with dynamic pricing according to peak time.

The project was considered a *success*, as citizens' human welfare in energy consumption increased through reduced electricity costs per household, improved reliability and robustness of the smart grid due to informed management of the peaks by the utility, and reduced emissions. A plus was the creation of new jobs in the area (Hedges, 2015).

4. Results

4.1. Foundations: Key properties of NKC citizen landscapes

We first translated the two basic properties of the NKC fitness landscape model introduced in Section 2 to the context of citizens adapting in complex decision environments (Billinger, Stieglitz, & Schumacher, 2014; Levinthal & Warglien, 1999; March, 1991; Simon, 1955). We conceptually modeled the basic properties, the rugged NKC citizen landscape and the citizens as searchers on those landscapes, through empirical sense making using our empirical settings. Table 3 summarizes the results. For both properties, it presents the results of our abstract *theoretical representation* in the NKC logic (column 1) as well as our *empirical reflection/representation* using the three instrumental case settings (column 2 to 4). These properties establish important foundations for our findings on the transparency effects in policy making since they establish the core assumptions needed to engage in sense making and causal reasoning through a co-evolutionary lens, both in an abstract as well as empirical way. We will discuss both properties briefly without repeating the table content.

4.1.1. Rugged citizen fitness landscapes

In the citizen context, the NK fitness landscape is best labeled as a citizen fitness landscape**,** which represents a "decision space" with all potential alternatives for combining different states of *N* and different policy-related decision attributes *p* (the axis) (Billinger et al., 2014). The attributes *p* are directly or indirectly modified by policy makers in their attempt to achieve a particular policy goal. Each decision attribute can take different states. While our empirical data would suggest that these attributes take multiple states, it is more difficult to visualize compared to landscapes with binary states (0 or 1). Thus, we chose binary states to visualize an exemplary citizen fitness landscape with $N = 6$ in Fig. 2.[6] It describes Citizen C#1's choice at time t_1, abstractly represented as a set of six decisions attributes [p1|p2|p3|p4|p5|p6], or [111010], if considering the binary character of *p*. The choice represents a location in the landscape and is associated with a particular fitness value – the potentially achievable human welfare - expressed as the height of the peak of the location.

In the accordance with the NKC model, the height is computed as the sum of each attribute's fitness contributions (Kauffman, 1993; Levinthal, 1997). Our cases did not provide insight into the exact fitness contribution of each attribute's *p* fitness contribution. However, we gained qualitative insights about attributes with highly positive and highly negative fitness contributions. For example, in the VCO case, the factor attribute *diagnosis* in the emergency room may have strong negative implication on human welfare (mostly due to *time attendance*) (see Table 3). Fitness values in a certain landscape may vary between 0 and a maximum achievable fitness value. While our empirical cases did not provide insight into the upper boundary for human welfare, we can assume that such a maximum level of fitness (or human welfare) exists. In Fig. 2, we depict the fitness value as a range between [0 to 1], given the binary nature of the landscape decision attributes *p*.

4.1.2. Citizens as local and distant searchers

Citizens are agents that search in their landscape with the goal to move to a location with a higher fitness value – a higher peak in the landscape. In our empirical context, citizens' goal is to achieve greater human welfare, e.g., in healthcare, energy, or transportation services. As boundedly rational individuals (Kahneman, 2003; March & Simon, 1958; Simon, 1991), they are locally intelligent, and thus, their preferred move is local (hill-climbing; introduced in Section 2). A local search move describes a minor behavioral change consistent with existing citizens' knowledge and routines. For example, in the VCO case, they would primarily be focusing on changing one attribute *p*, such as the *monitoring for prevention* (e.g., e-health remote monitoring for blood and sugar parameters instead of doctor visits) but they would not change any other attributes (e.g., their *treatment* services). Such a local search move is visualized in Fig. 2 for citizen C#1. He moves from the location at time t_1 [111010] to a location at t_2 at [111011], changing only *p1* (e.g., *monitoring for prevention*), leading to a slightly higher fitness value. This is because human welfare increases in terms of the subjective value of the effect of the service in the personal health condition, including the estimated waiting time for service delivery and estimated costs. Only in rare occasions would they engage in a distant search move and change multiple decision attributes, e.g., by taking their *prevention* monitoring measures at home using an e-health solution, having been *diagnose*d remotely at home with e-health and also using e-health *homecare*. Such a distant move with changes in three

[6] In this visualization, we translate the *N*-dimensional binary space of the NK model into a 2-dimensional one in which each dimension has $2\,N/2$ points that are ordered in an ascending way on two axes. For example, for $N = 6$, a potential design alternative is [000101]. We represent this 6-dimensional solution in two dimensions by representing one-half of the design alternative on the x-axis, and the other half of the design alternative on the y-axis. This gives us the opportunity to create a 3-dimensional landscape.

Table 3
Modeling of basic properties (and attributes) through theoretical representation in NKC logic and empirical representation.

Theoretical representation of basic properties in NKC	Empirical representation Case 1: e-Health Program in VCO	Empirical representation Case 2: Stockholm Congestion Charge Program	Empirical representation Case 3: Kansas City Smart Grid Program
Property 1: Rugged Citizen Landscapes			
1. Rugged citizen landscapes. The citizen fitness landscape represents a "decision space" with all potential alternatives for combining different states of *N* different policy-related decision factors *p* (the axis)	The e-health citizen landscape represents the decision attributes that policy makers directly modified or indirectly affected when designing and implementing the e-health pilot. It contains all potential combinations of multiple policy-related healthcare decision attributes.	The congestion charge citizen landscape presents all potential combinations of multiple mobility decision attributes, modified by a new environmental charge system for reducing congestion. Citizens combine those attributes when making choices.	The smart grid citizen landscape represents all decision attributes that citizens combine when making home energy consumption choices. Policy makers 'architect' this decision space through the design of a smart grid solution for the civic community.
2. Policy-related choice attributes Policy-related choice attributes *p* are those factors that affect a citizen's choices and behavior related to the policy goal. Each choice attribute *p* can take different states. In its simplest form, the NKC model assumes binary states (0,1).	Examples of key decision attributes modified and related to policy: 1. Monitoring for prevention (e-health/remote, phone, doctor visits) 2. Diagnosis (emergency, outpatient care, e-health/remote) 3. Referral (social network, personal operator via e-health system) 4. Treatment (outpatient care specialist, emergency room) 5. Home care (physical, e-health) 6. Consulting (phone, e-health, decentralized) 7. Insurance (private versus public) 8. Patient feedback (offline, social media)	Examples of key decision attributes modified and related to policy: 1. Mode (public versus private transportation services) 2. Route (including arterials) 3. Charge associated with route (free, toll-based) 4. Departure time (peak time, at night, others 5. Travel destination 6. Travel duration 7. Expected travel costs (based on experience, real-time) 8. Environmental attitude	Examples of key decision attributes modified and related to policy: 1. Day-to-day energy consumption (based on experience, based on *smart consumption* feature with smart pricing) 2. Appliance & system control (manual, with programmable thermostat, automation) 3. Energy consumption feedback (no feedback, real-time individual, real-time social) 4. Use of equipment (no energy efficient equipment, investment into energy efficient equipment like water & heating, lighting controls, refrigeration, air compression) 5. Energy generation (no generation, some generation, high generation) 6. Tax incentives 7. Timing of energy consumption 8. Automation control features
3. A location in the landscape. A location describes a citizen's placement in the landscape based on the combination of *N* decision attributes *p*1, *p*2, …*pN* that a citizen has selected. Two locations that are very closely related to each other have very similar decision attributes.	A citizen in VCO at a particular point in time chooses a certain combination of decision attributes *p*. For example, she might choose to use the emergency room for *diagnosis*, and go to an outpatient care specialist to *treat* her symptoms that someone in the social network has recommended (*referral*).	A citizen in Stockholm at a particular point in time might choose to drive by car (*mode*), choose a toll-based route (*charge associated with route*), and drive to the city center (*route*) during peak times (*time*).	A citizen in Kansas City regulates *temperature & lighting* ad-hoc, using standard *equipment*, and has insight about his *predicted energy consumption* on a monthly basis.
4. The fitness value associated with location: The fitness is the weighted sum of the fitness contribution of all decision attributes chosen by the citizens. The higher the fitness value, the greater the individual human welfare in focus by the policy goal.	Each citizen e-health-related choice is associated with a certain fitness value associated with the location (i.e., individual welfare, measurable in terms of subjective value of effect of the service in personal health condition, including the estimated waiting time for service delivery and estimated costs).	Each citizen's mobility choice related to the congestion charge system is associated with a certain fitness value associated with the location (i.e., individual welfare measurable with the subjective value of time, estimated cost spent to commute to the city center and the environmental effect).	Each energy consumption choice is associated with a certain individual welfare, (i.e., measurable in terms of subjective value of estimated cost spent in energy consumption while maintaining quality of life)
Property 2: The Citizens as Landscape Searchers			
5. Local search (hill-climbing) versus distant search (long-jumps). • *Local search:* When hill-climbing, a citizen only considers locations nearby. They are more certain, because they only require a change in ONE decision attribute. • *Distant search:* A long-jump implies a major change a citizen's choice. They move to a more distant location by changing multiple (at least three) decision attributes. Citizens as behaviorally-bounded searchers prefer local search, unless there is information available that warrants a distant move.	Examples of local and distant search away from location described in 3. are: • Local search: The citizen decides to switch to remote-based monitoring of his blood sugar (monitoring for prevention) but does not change any other healthcare-related decision attributes. • Distant search: The citizen chooses an e-health solution for monitoring for prevention, diagnosis and home care. She/he changes 3 attributes.	Examples of local and distant search away from location described in 3. are: • Local search: Instead of driving during peak hours, the citizen departs earlier to save time and money. The person only changes the departure time. • Distant search: The citizen switches to public transportation (mode), and leaves earlier in the day (departure time), and also increases his/her attention to environmental impact (environmental awareness). She/he changes 3 attributes.	Examples of local and distant search away from location described in 3. are: • Local search: Citizens use smart consumption feature and adjust her energy conservation behavior slightly (e.g., she washes her clothes at night) • Distant search: The citizens decide to buy energy efficient equipment (e.g., a new water heater) and installs energy generation products (e.g., solar panels) to produce energy during peak hours.
Sources: Billinger et al. (2014); Levinthal and Warglien (1999); March (1991); Simon (1955).	*Sources*: Albert, Shevchik, Paone, and Martich (2011); Central European Living Lab for Territorial Innovation (2019); Ferro, Loukis, Charalabidis, & Osella (2013b); Misuraca, Rossel, and Codagnone (2011); Pillon (2015); Ross, Stevenson, Lau, and Murray (2016); Rota and Santafede (2012); Tennant et al. (2015).	*Sources*: Börjesson, Eliasson, Hugosson, and Brundell-Freij (2012); Eliasson Rhodes (2012); Eliasson (2008, 2014); Eliasson and Jonsson (2011).	*Sources*: Goulden, Bedwell, Rennick-Egglestone, Rodden, and Spence (2014); Hedges (2015); SmartGrid (2011); Vojdani (2008); Zhang, Liu, Sayogo, Picazo-Vela, and Luna-Reyes (2016).

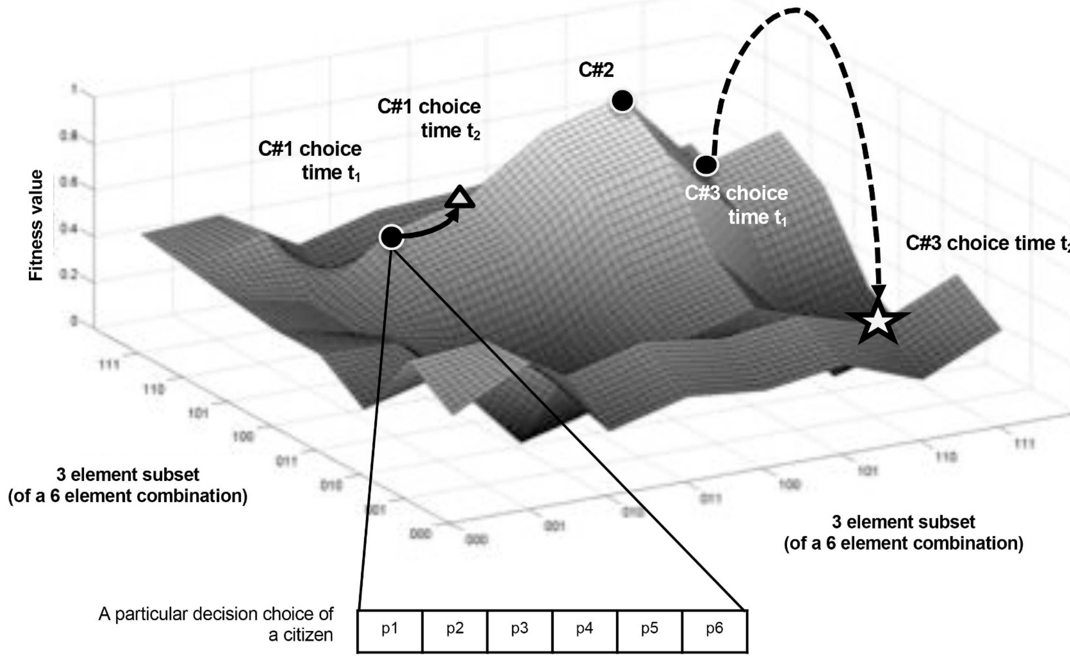

Fig. 2. Rugged citizen fitness landscape with citizens as searchers.

attributes is visualized for citizen C#3, who takes a long-jump and moves from [110111] to [001111].

4.2. Transparency in policy making: an empirically validated co-evolutionary framework

Having established the two basic properties of an NKC citizen fitness landscape, we turn to the generative mechanisms that explain how transparency impacts effective policy making. We have identified those mechanisms triangulating between *theoretical representation* using general theoretical arguments of the NKC landscape model (Kauffman, 1993; Levinthal, 1997; Levinthal & Warglien, 1999; McKelvey, 1999) as well as *empirical reflection* and *validation* using instrumental cases with longitudinal data. Indeed, the empirical analysis, guided by theoretical assumptions, was essential for identifying the generative mechanisms. We have summarized our results in a co-evolutionary framework in Fig. 3, and detail our theoretical and empirical results on the generative mechanisms in Table 4.

Fig. 3 describes the causal logic of co-evolutionary adaptation through the CAS lens, in which citizens as searchers of their landscapes co-evolve. Our explanatory focus is on the *effectiveness* of policy making, defined as the success in enabling citizens to adapt in alignment with the policy goal to produce *greater collective human welfare* for their citizens as a whole (Box 1).

In line with basic assumptions of CAS (see Section 2.2) and our theoretical foundations (Section 4), the collective-level outcome emerges from the individual adaptation of the citizens who engage in iterative search moves (Box 2) on their interdependent citizen landscapes. Citizens search in parallel across their individual citizen landscapes, which represent the choice architecture related to a particular policy goal. The outcome of these co-evolutionary processes, each taking place in an individual local context, aggregates into a welfare at collective level. This *generative* aspect is *not* the result of a priori design, but it surfaces from local search processes (Gell-Mann, 1995). A co-evolutionary view towards complexity suggests that there are three sources of complexity that affect the nature of co-evolutionary adaptation locally via the shape of the citizens' landscapes: (1) internal dependence in an individual landscape (represented with the attribute *K*) which we label as *individual decision interdependence*; (2) *decision bias* inherent to a citizen's search heuristic; and (3) external interdependence between different citizens (represented with the attribute *C* in NKC) which we refer to as *collective decision interdependence*. These three sources can cause so-called "complexity catastrophe" (Kauffman, 1993). Referring back to our citizen NKC fitness landscape conceptualized earlier (Fig. 2), this describes a condition where citizens get "trapped" or settle on locations with low peaks that do not bear a high individual welfare, compared to the highest peaks in the overall landscape. Such conditions are socially undesirable, in particular, if such complexity catastrophes cannot be "reversed" because citizens are unable to adapt to the information available about their citizen landscapes. We will elaborate on each source of complexity in the next section.

Our framework conceives transparency as an integral part of *iterative policy making* throughout the whole policy cycle (Box 3). In our empirical analysis we learned that transparency, as a digitally-mediated relationship between policy makers and citizens, is often present during the early stages of the policy cycle of discovery (including problem definition and policy development) as well as later ones (including implementation and evaluation) (Janssen & Helbig, 2016). In accordance with an integrative view towards transparency in prior literature (see Section 2.1), citizens (and their citizen landscapes) are the primary object of transparency, whose behaviors are observed by policy makers and other the citizens themselves (or both). Thus, as visualized with the arrows in the Fig. 3, if there is visibility of the citizen landscapes (and the citizens behavior on them), there is also transparency about the sources of complexity in these landscapes. Our theoretical engagement with the NKC fitness landscape and our empirical analysis suggest that there are three types of transparencies, each relating to a particular source of complexity.

Our casual logic to explain the effect of transparency is articulated through generative mechanisms, that is policy-making processes that utilize transparency to modify the citizen landscapes and the information available to citizens about their landscapes (Boxes 4a and 4b). Each of the three transparencies affects co-evolutionary adaptation via two complementary *generative mechanisms*: (1) *Orchestration* for local search via fitness landscape tuning *(Box 4a)* (Janssen & Helbig, 2016); and (2) *Social learning* for distant search as different variants of "social nudging" (Box 4b) (Bandura, 1965; Benkler, 2006; Sunstein, 2014). While these

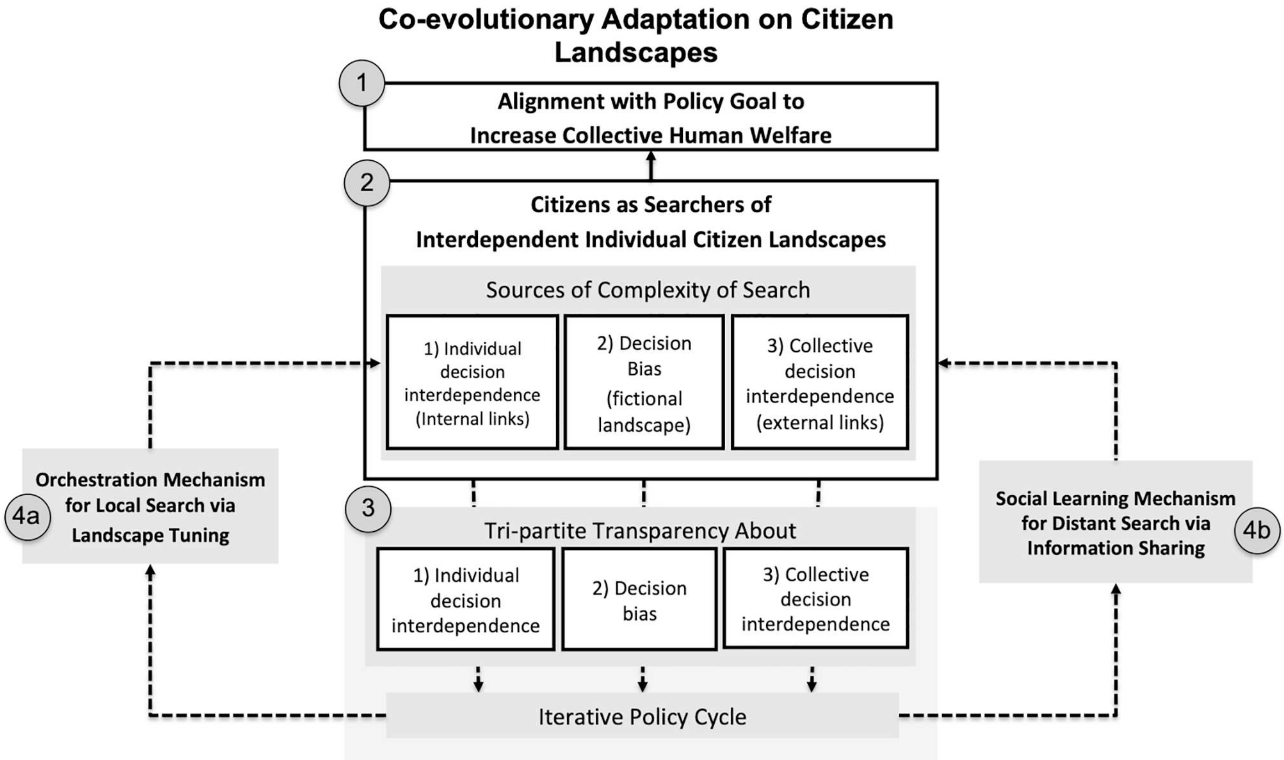

Fig. 3. Co-evolutionary framework of transparency in policy making.

mechanisms unfold differently, depending on the type of transparency, they share general explanatory principles. Orchestration for local search via fitness landscape tuning (Levinthal & Warglien, 1999) refers to the policy makers' attempts to tune the citizen landscape so that it becomes *smoother*, allowing citizens to safely move towards the peak using *local search*. The generative mechanism of social learning for distant search is a form of a "nudge" (Sunstein, 2014) that exploits the constituting role of social information in decision making (Bandura, 1965; Benkler, 2006; Sunstein, 2014). Our view of nudging through social information considers the evolutionary and adaptive nature of human behavior (Levinthal & Warglien, 1999; Simon, 1990; Sloman & Fernbach, 2018) in which information about citizens with very different experiences may represent an essential capacity for citizens to learn from each other. Social nudging can change their behavior more fundamentally using *distant long-jumps* on their landscapes (Levinthal & Warglien, 1999).

Table 4 summarizes the results that explain the transparency effects with 6 generative mechanisms, grouped into the three transparencies (each relating to one particular source of complexity). For each transparency and its related generative mechanisms, we present our results of the *theoretical representation* of the NKC properties (left column) and the *empirical sense making* (right column). We will discuss each transparency and its related generative mechanism in the following sections 4.3. to 4.5.

4.3. Transparency about internal decision interdependence and its generative mechanisms

The *first transparency* relates to the internal decision interdependence inside an individual citizen landscape. We will first define it and then articulate two generative mechanisms that explain its positive effect on positive co-evolutionary adaptation.

4.3.1. Transparency about individual decision interdependence

Our study suggests that one form of transparency relates to the observability of interdependencies among the different choice attributes in a single citizen landscape, created and modified by policy makers (Billinger et al., 2014; Sunstein, 2014). Our citizen landscape is best represented as the observability of: (1) the links among the N policy-related choice attributes p in the landscape (Kauffman, 1993; Levinthal, 1997; Levinthal & Warglien, 1999; McKelvey, 1999); and (2) the (negative) effect of such interdependence in citizens' human welfare when they search on the landscape. In the original NKC model, this is referred to as epistatic interactions in the fitness landscape (Kauffman, 1993; Levinthal, 1997).

Having transparency about individual decision interdependence provides important insights into one source of complexity that stems from the shape of the individual citizen landscape (Levinthal & March, 1981; Levinthal & Warglien, 1999) simply because it makes the surface, that is the ruggedness, of an individual citizen landscape observable. From a policy makers' point of view, it is desirable to have zero or at least low interdependence because it stabilizes the adaptation of the citizens on their landscapes. If individual decision interdependence is zero or low, a citizen's fitness landscape is single peaked like in Fig. 4. Such smooth landscapes "gently lead the [citizens] to the maximum" (Levinthal & Warglien, 1999, p. 345) from any starting point. It allows citizens to utilize their search preference for local search. Since they can discriminate between immediate neighborhood locations (choices) that are leading uphill to greater human welfare and those that lead downhill to a lower human welfare, they eventually reach the maximum on smooth landscapes. However, we learned in our study that many citizen landscapes are not always smooth, in particular if policy makers introduce new and modify existing decision attributes through the policy solution. If citizen landscapes have many interdependencies between the N decision attributes, the landscape becomes more rugged or multipeaked because two neighboring solutions, even though they are very similar in their decision attributes, are associated with very different fitness values. A more rugged citizen landscape with 10 decision attributes, and 9 interdependencies between a particular decision attribute *p1,..p10* is illustrated in Fig. 4 below. This visualization

Table 4
Summary of findings on generative mechanisms explaining transparency effects.

Transparency		Generative Mechanisms		Sources
Theoretical Def. in NKC	Empirical Description	Theoretical Explanation in NKC	Empirical Explanation – Highlights Only	
4.3.1 Transparency about individual decision interdependence describes the observability of (1) information about the interdependence between *N* decision attributes inside individual citizen landscapes (*K*) and the), and (2) human welfare implications of such interdependence.	In the **e-health Program in VCO**, policy makers observed high interdependence between decision attributes of monitoring for prevention, diagnosis, treatment services or home care. A choice including e-health may lead to a significantly lower human welfare if citizens may not combine it with their existing healthcare services	**4.3.2 Orchestration mechanism for local search via real landscape tuning** describes the process of how policy makers use individual decision interdependence transparency to tune down the *K* interdependence inside the citizen landscape and create a visible unambiguous path towards a single peak.	In the **e-health Program in VCO**, policy makers tuned the e-healthcare landscape by ensuring compatibility of an e-health choice in a particular decision attribute (e.g., remote monitoring of blood sugar) with any other decision attributes (e.g., using an existing treatment service providers). Citizens could easily "mix-and-match" their health services, ensuring continuity through incremental behavioral change with little ambiguity (e.g., they could keep their treatment service providers).	Albert et al. (2011); Ferro et al. (2013b); Misuraca et al. (2011); Ross et al. (2016); Rota and Santafede (2012); Tennant et al. (2015)
		4.3.3 Social learning mechanism for distant search via information sharing in real landscapes describes the process of how policy makers observe and share selected information about other locations chosen by other citizens to encourage citizens to take "long-jumps" and learn from them.	In the **e-health Program in VCO**, policy makers shared social information about citizens residing in distant locations on their landscape. They encouraged citizens to learn from others via social features of the governmental platform; social proof about others' choices and their benefits encouraged more fundamental behavioral changes (e.g. shifting from traditional services to a complete e-health portfolio).	
4.4.1 Transparency about decision bias is defined as the observability information about (1) fictional fitness values associated with locations in individual citizen landscapes and (2) human welfare implications of such fictional peaks.	In the **Stockholm congestion charge program**, policy makers had transparency about citizen's decision biases because they observed that citizens, intuitively, did not associate a benefit with the introduction of a congestion charge (fictional peak); such biases negatively affect behavioral change because citizens were unable to perceive the real benefits of a choice involving a charge (undifferentiated landscape)	**4.4.2 Orchestration mechanism for local search via fictional landscape tuning** describes how policy makers utilize transparency about decision bias to tune fictional landscapes into one that encourages local search. To do so, they transform the "undifferentiated" fictional landscape into one that makes incremental welfare improvements visible for citizens (positive gradient).	In the **Stockholm Congestion Charge Program**, policy makers tuned the biased decision landscape by designing a simple time-dependent congestion charging system and digitally-enabled real-time feedback about benefits (and losses) associated with the charge. This allowed citizens to align with the policy easily because their doubts about the charge disappeared when they "saw" and "experienced the benefits from incrementally changing their transportation habits incrementally (e.g., changing the departure time when driving by car in order to pay a lower charge during off-peak times).	Börjesson et al. (2012); Eliasson (2012); Eliasson, (2008, 2014); Eliasson and Jonsson (2011).
		4.4.3. Social learning mechanism for distant search via information sharing in fictional landscapes describes how policy makers may use information about decision biases to uncover distant regions on fictional landscapes. They share fictional locations of other citizens so that citizens are encouraged to learn from them.	In the **Stockholm Congestion Charge Program**, policy makers shared social information gathered from citizens periodic on-going evaluations to nudge more reluctant citizens into changing their behavior more fundamentally (e.g., switching from car to public transport). They shared other citizens' transportation choices and also others' perceived attitudes towards the charge (in the sense of a fictional peak) encouraging citizens to learn from each other.	
4.5.1 Transparency about collective decision interdependence is defined as the observability of information about (1) collective decision interdependence between the different individual citizen landscapes (*K*) and (2) the	In the **Kansas City Smart Grid Program,** policy makers observed decision attributes that create interdependencies and social dynamics (energy consumption habits, device control, energy generation, equipment choice); learned about the adverse effects (e.g., reliability of the grid,	**4.5.2. Orchestration mechanism for local search via tuning of dancing landscapes** describes the process of how policymakers can utilize the observability of collective decision interdependence to reverse the negative self-reinforcing processes created through collective	In the **Kansas City Smart Grid Program**, policy makers utilized their insights about collective interdependence to iteratively redesign the smart energy infrastructure with features like smart consumption and smart display: They triggered citizens to act less	Goulden et al. (2014); Hedges (2015); SmartGrid (2011); Vojdani, 2008; Zhang et al. (2016).

(*continued on next page*)

Table 4 (*continued*)

Transparency		Generative Mechanisms		Sources
dynamic change in a landscape caused by a move on the other one.	availability of green resources) if citizens engage in habit-driven energy consumption not considering their collective interdependence.	interdependence by creating a form of illusionary hill-climbing encouraging all citizens in parallel to act more collectively instead of individualistically (climbing down the hill).	selfishly using smart pricing and smart displays. Citizens were informed on the benefits of off-peak consumption, shifting their choices away from their energy consumption habits. Without even anticipating it, they acted collectively (and benefited from it).	
		4.5.3. Social learning mechanism for distant illusionary search via information sharing on dancing landscapes describes how policy makers utilize information about dancing landscapes to encourage citizens to learn from others and align with the collective goal. Such collective awareness creates socially created illusions of a welfare benefit, encouraging individuals to engage in more distant search. Eventually such illusions translate into real benefits.	In the **Kansas City Smart Grid Program**, policy makers used transparency about collective interdependence to share collective energy consumption information through a customer web portal and smart home devices. Through social information, citizens learned about community's performance in meeting the collective energy conservation goal. Furthermore, they learned about what others were doing in their homes to align with this goal, shifting the attention from the individual to the collective goal, and triggering more fundamental behavioral change (buying energy-efficient equipment, installing a new solar cells).	

describes the shortcomings of local search for human welfare.

On a rugged landscape, if a behaviorally bounded citizen tries to use his preferred local move from Location A to any immediate neighboring location, the person might only observe downward paths as the peak is surrounded only by valleys. The citizen cannot "see" better choices, like Location B, since that is beyond what can be perceived. As a result, citizens easily get trapped on a suboptimal peak, with significant negative implications for human welfare overall.

In the VCO *E*-health program, for example, policy makers gained transparency about such individual decision interdependence with the help of the "Padgets" platform, which allowed mining and analyzing perceptual, communicative, and behavioral data throughout the policy cycle (Ferro et al., 2013). They could learn that the introduction of an e-health choice may strongly interact with other decision attributes related to the use of healthcare services by citizens. For instance, where should the citizens go for *treatment*, *diagnosis* (whether performed in an emergency room, outpatient care or e-health), *homecare,* (whether through e-health or the traditional physical homecare, or referral, where a "personal operator" could also provide professional recommendations)? Using e-health meant that citizens would be able to use interactive *remote diagnosis* and remote *monitoring* for *prevention* (e.g., blood pressure, sugar levels and other parameters). However, going the e-health route may not always have been compatible with many other previous choice attributes (e.g., keeping the current *outpatient care* doctor) and *expenses* (free service versus potential charge for future e-health deployment options). If healthcare professionals were not part of the e-health offering, a citizen would not have been able to combine e-health with his/her existing healthcare services. For example, they would not be able to have remote monitoring for *prevention* via e-health with their existing doctors, but instead would have a "personal operator" with access to their diagnosis. Furthermore, the use of an emergency room for diagnosis of nonacute conditions, a preferred choice by many citizens, seemed not to be compatible with the e-health option, as it would replace it. As a result, the e-health decision landscape of an individual citizen became "rugged" and a single local move (one change in a decision attribute) could lead to a significant drop in a citizen's fitness. For example, if citizens choose e-health for monitoring their health (e.g., blood, sugar parameters) but were unable to integrate such monitoring into their treatment service with their traditional doctors, citizens move down the hill (Rota & Santafede, 2012).

But how can policy makers use the insights about the ruggedness of an individual citizen landscape to create levers for behavioral change in line with the policy goal? Our study suggests that transparency effects can be explained by generative mechanisms and processes that stabilize co-evolutionary adaptation on fitness landscape. We explain these next.

4.3.2. Orchestrating mechanism for local search via landscape tuning

First, by tuning down some of the interdependencies between decision attributes modified by a new policy (and those affected by it) policy makers can stabilize the adaptive search processes of the citizens and create a single peak landscape with lower K. On such citizen landscapes, citizens may easily adapt towards greater human welfare irrespective of their current location because they have access to *unambiguous information feedback* in their immediate neighborhood on their landscapes that allow them to smoothly move to the basin of attraction (Levinthal & Warglien, 1999, p. 34), a term used in complexity theory for describing the peaked area in the landscape with the highest welfare. In other words, policy makers need to transform the landscape into one that has a clearly visible single peak, where surfaces afford *intuitive* decisions with a low cognitive effort (Kahneman, 2003), since the peak can be reached with local moves (hill-climbing). We identified two specific tuning actions.

Policy makers may use transparency about K to iteratively "reengineer" their policy solutions so that attributes modified by such solutions become compatible with other attributes (Weerakkody, Janssen, & Dwivedi, 2011). In NKC language, this is also referred to as

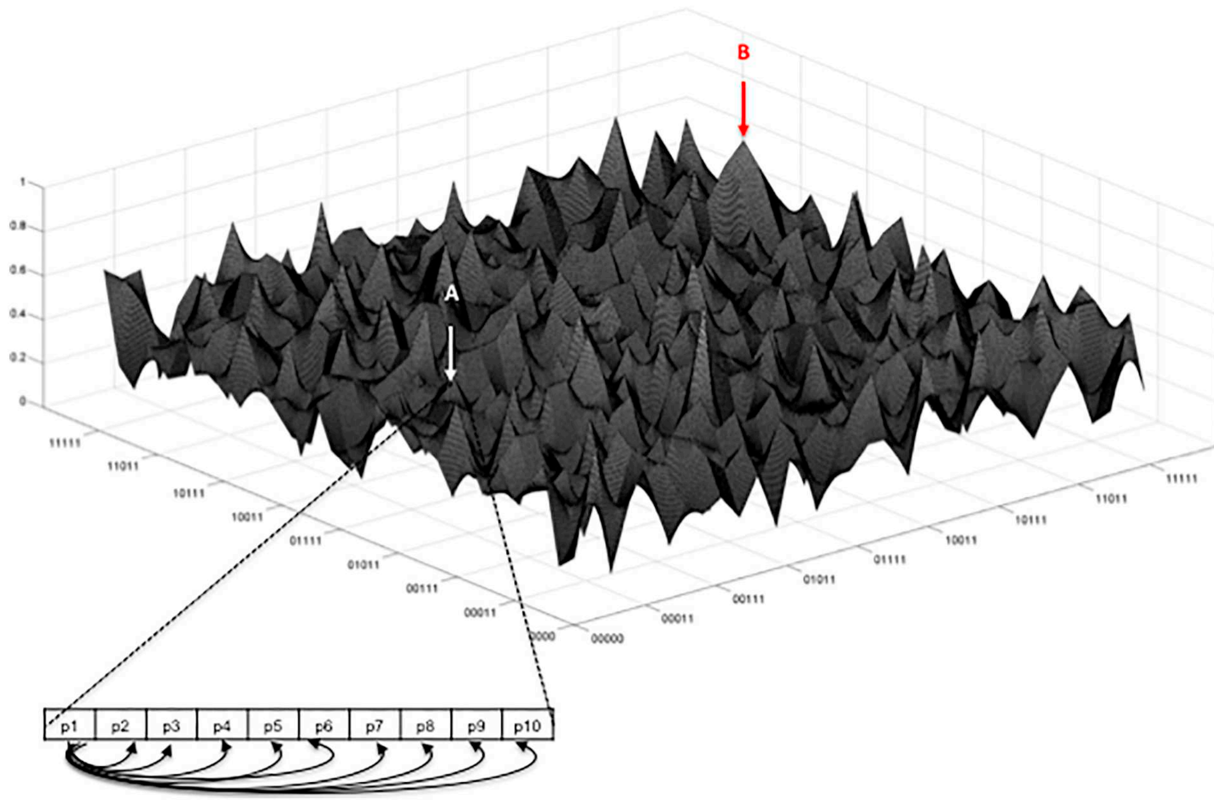

Fig. 4. Fitness landscape with 10 decision attributes and 9 interdependencies.

"decoupling," which makes behavioral change safer and somewhat more predictable. In the VCO case, policy makers created compatibility between the e-health option and other important healthcare choice attributes such as *diagnosis, treatment, homecare, and referral (*see Table 3*)*. Compatibility of choices between the e-health option and other healthcare decision attributes affords continuity in behavior, irrespective of their particular choice (or location). For example, an e-health monitoring solution for control of blood sugar parameters can be easily combined with a *treatment* service from a specialist since this specialist supports e-health in their practice.

Second, we learned that policy makers may also use constraints in the landscapes in order to visibly guide citizens on their path to climb towards the peak with local moves (hill-climbing). We define constraints in accordance with literature on complexity and decision architecture (Weerakkody et al., 2011) as the mandatory stage of certain decision attributes that cannot be modified by citizens, the searchers of the landscape. For example, in the VCO e-health program, policy makers established a personal operator to facilitate the remote service (Ferro et al., 2013). This personal operator, a mandatory choice, guided citizens to a location on their landscapes that made local search easy. The personal operator facilitated the decision-making process of citizens hesitating about what to do next after using the different e-health devices (e.g., blood, sugar and other health parameters). Thanks to the personal operator, citizens could iteratively adjust their healthcare choices, eventually leading to greater human welfare (e.g., avoiding waiting time in emergency rooms when avoidable) and continuity of care. Both efforts were realized at multiple stages of the iterative policy cycle (e.g., during and after the pilot program to design the eventual deployment in the Piedmont region), allowing policy makers to iteratively discover and evaluate the most robust surface of the individual citizen landscape. Such tuned, robust landscapes provide unambiguous guidance so that citizens can make simple and "safe" choices that increase their individual welfare (i.e., reducing waiting time) in line with the policy goal (i.e., to significantly reduce the number and frequency of visits to emergency services and specialist outpatient services).

4.3.3. Social learning mechanism for distant search via information sharing about citizen landscape

Complementary to individual fitness landscape tuning, our modeling indicates that individual decision transparency should support policy makers to create "social proof" (Lee, Tsohou, & Choi, 2017) of the benefits of moving to a distant location for greater fitness value. If citizens are informed about what others do, they can integrate such moves with their own experiences. Such experiences are essential for individuals to mutually exploit and explore their own and others' experiences. Thus, a co-evolutionary view towards nudging does not make citizens "randomly credulous" but instead offers them a generative capacity to evolve towards greater fitness. It triggers social adaptation that allows citizens to better cope with the uncertainty when engaging in distant search (Billinger et al., 2014) or, in other words, a more fundamental behavioral change.

In the E-health Program in VCO, policy makers made use of such social learning. They used data collected from the "Padgets" platform and shared social information about the welfare benefits experienced by citizens who participated in the e-health pilot. Through their opinions, citizens shared their feedback about their experience within the pilot and how e-health was compatible with a range of different decision attributes, including *diagnosis, treatment, or homecare service.* Such social insights may encourage others to significantly change their behavior choices and also be willing to adopt an e-health service in the future, thus changing various decision attributes but without blindly copying from others. The benefits experienced from such e-health choices (e.g., no waiting time in emergency room, higher quality of diagnosis) outweighed their perceived "costs" for *e-health services* (e.g., reduction of time with a doctor, technical barriers). They even expressed their willingness to pay for e-health even though they were reluctant in the first place (Ferro et al., 2013). Thus, social nudging enabled citizens to take more distant moves on their landscapes and become more flexible and generatively adapt towards greater welfare through the diversity of local knowledge that policy makers made visible and observable.

4.4. Transparency about decision bias and its generative mechanisms

We will next define the second type of transparency and explain its generative mechanism for stable co-evolutionary adaptation.

4.4.1. Transparency about decision bias

The second type of transparency relates to the observability of citizens' *decision bias* when they search for greater fitness using search heuristics (Anderson, 1999; Gell-Mann, 1995; Kauffman, 1993). In simple words, such a *decision bias* (Kahneman, 2003, p. 1463) leads to an *incorrect* evaluation of the welfare of a certain location.[7] If policy makers modify or add a new decision attribute when developing a policy, citizens draw associations between their current choice or location and the target one (Gavetti & Warglien, 2015; Tversky & Kahneman, 1974). Such associations, however, lead to wrong conclusions that do not reflect the actual welfare associated with the choice. Essentially, citizens do not perceive an actual peak but assume that the target location has lower or equal welfare compared to one's current choice. As such, they do not consider a move. Our empirical data suggests that citizens perceive such fictional landscapes. And they may lead to unexpected negative welfare implications in the sense of a complexity catastrophe where citizens settle on socially suboptimal choices (McKelvey, 1999). The reason is as follows: If citizens search a fictional landscape, citizens fail to consider moving to a higher peak because their fictional landscape prevents them from actual discriminate options for increasing their fitness through local search (hill-climbing), or more distantly, through a long-jump.

In the Stockholm Congestion Charging Program, policy makers used social media, IoT, and ongoing evaluation exercises throughout a highly iterative policy cycle to collect insights into the citizens' fictional landscapes that reflect their misinterpretation of the benefits of a congestion charge. They developed several versions of such a congestion charge instrument, for which they changed the real citizens' landscape by modifying certain decision attributes (e.g., the *amount* of the charge, the *time of traveling* affected by the charge, the *environmental information* communicated about the impact of the traffic reduction) and evaluated citizens' perceptions and actions before and after testing the charge. During this iterative process, policy makers learned that citizens tend to be more sensitive to negative impacts of a behavioral change in alignment with the charge without considering its potential benefits in terms of human welfare (e.g., no delay when driving a car or environmental benefits) (Avineri, 2012). In the language of our model, they might have perceived a distorted fictional landscape where the fictional fitness value associated with a change, for example, a move to a new location (choice), is much lower (e.g., cost of the charge when choosing the mode of driving by car and paying for a toll-based road), compared to the objectively achievable one (e.g., actual benefits regarding the traffic reduction and positive environmental effects). This bias results in the fact that a real "peak" associated with a choice involving a charge is not perceived (Eliasson & Jonsson, 2011). Having transparency about such biases shows that policy makers had insights into the fact that citizens lack a clear gradient for hill-climbing and also had new information that warranted a distant long-jump.

4.4.2. Orchestrating mechanism for local search via fictional landscape tuning

First, we learned that policy makers can utilize transparency to tune the fictional landscape (Levinthal & Warglien, 1999) to transform the "undifferentiated" fictional landscape into one that has a clearly visible single peak, one we referred to earlier as having a basin of attraction (Levinthal & Warglien, 1999). For example, in Stockholm Congestion Charging Program, policy makers developed and evaluated a time-dependent charge in a way that it tuned the fictional landscape to have a clear visible "basin of attraction." First, the charge between SEK 10 and 20 for different time intervals (roughly US$1 to $2) (Eliasson, 2008) and a maximum daily charge of total SEK 60 (roughly US$6.50) was not only small but also compatible with various decision attributes in the citizens' landscapes (e.g., citizens could still take the same route, at the same time of the day if they paid the charge). Second, the charging scheme was simple in order to make it easy to understand (e.g., one single charging cordon, with the same charge at all entry points and same in both directions). Third, the charging system created real-time feedback about the person's welfare implications. They could immediately observe the cumulative charge per day and month as well as their environmental impact (Eliasson & Jonsson, 2008). These three factors tuned the fictional map in a way that a citizen who was pondering whether to just drive at the originally intended time, or considered an alternative, simple option (e.g., changing their departure time) had unambiguous insights about the benefits and costs prior to making such a local move (hill-climbing). Apparently, the fictional landscape surface was tuned so "smoothly" that it allowed citizens to make intuitive decisions. Unambiguous information about the welfare associated with a hill-climbing move (e.g., just leaving a little earlier) triggered such a move and could also be immediately experienced: streets were empty and congestion dropped by 30% (Eliasson & Jonsson, 2011).

4.4.3. Social learning mechanism for distant search via information sharing about fictional landscapes

Complementary to fictional fitness landscape tuning, we learned that policy makers, by sharing insights about the perceived positive welfare effect, can create an "illusion" of how much citizens are "losing" if they are not changing their behavior and aligning with the behavior of others (Kahneman, 2003; Rendell et al., 2011; Tversky & Kahneman, 1986). For example, when iteratively designing and evaluating the Congestion Charging Program, policy makers publicly shared the Stockholm citizens' positive experiences towards the congestion charge based on a survey and data analysis after the first pilot program of the charge (Eliasson, 2014) which emphasized the importance of the environmental benefits of the charge (e.g., Börjesson, Eliasson, Hugosson, & Brundell-Freij, 2012; Eliasson, 2008; Eliasson, Hultkrantz, Nerhagen, & Rosqvist, 2009). Such insights about others' perceived welfare implications (via environmental benefits) may explain why some (not all) citizens engaged in a more fundamental change (long-jump or distant move). Instead of just driving a little earlier, about 15% of the car drivers who typically "crossed the toll cordon" switched to public transport, which implied changing the time of departure, route, travel duration, among other decision attributes (Börjesson, Eliasson, & Franklin, 2012; Karlström & Franklin, 2009).

4.5. Transparency about collective decision interdependencies and its generative mechanisms

Our study shows that a third type of transparency of *collective decision* interdependence is essential to generatively respond to the third complexity source, namely the links between different citizen landscapes. We will next define this transparency and then discuss its generative mechanisms.

4.5.1. Transparency about collective decision interdependencies

The third type of transparency relates to the observability of information about the interdependencies between multiple individual citizens' choices that exist in so-called social dilemma conditions

[7] It is important to note that not all search heuristics automatically imply a bias; for a more detailed discussion on this, we refer to (Gigerenzer & Todd, 1999).

(Kauffman, 1993; McKelvey, 1999). A social dilemma describes the situation in which the individual's and the group's welfare benefits accrued from a common pool of resources are misaligned: Citizens act selfishly, following their self-interests in contributing and using the common pool of resources. However, due to collective interdependence, such individualism can emerge into socially suboptimal outcomes as soon as the resources become scarce or less valuable (Glance & Huberman, 1994; Levinthal & Warglien, 1999; Ostrom, 1996). In the Smart Grid Program in Kansas City, policy makers faced a social dilemma. The community of citizens participating in the Smart Grid pilot project affect each other in both producing and utilizing a common pool of distributed energy resources (Wolsink, 2012), including fossil (coil, oil, natural gas), electric, and renewable sources (i.e., solar, biofuel), managed through a *smartSubstation* that integrates and distributes them (Wakefield & Hedges, 2010). However, the amount of clean energy available from such a collective production at a particular point of time is not unlimited (Rhodes, 2012). Thus, if many citizens act selfishly at a particular time and extensively consume energy through heating, cooling, and lighting during peak times (e.g., they all cook, wash, and watch TV during evening hours), without considering the implications of the collective pool of energy resources, the grid can easily reach its limits in terms of availability of resources, in particular the clean ones. Such selfish behavior negatively affects the welfare of the group as a whole: The demand of energy exceeds the availability of clean energy resources (e.g., solar, wind, etc.), leading to increased need to draw from fossil and electric power. Overall, the reliability of the grid is at risk, and the community's goal to be "green" (and eventually realize net-zero production) cannot be met. The natural tendency of humans to often unconsciously focus on their own benefits, simple because of routines and habits learned in the past (e.g., washing a little later at night, or producing instead of consuming energy during peak times), creates a negative social dynamic that is difficult to be reversed.

In our NKC modeling, such social dynamics with negative self-reinforcing mechanisms result from the negative *C* interdependencies between citizen landscapes, that is, the degree of decision attributes that cause social dynamics to emerge (Kauffman, 1993; Levinthal & Warglien, 1999; McKelvey, 1999). The greater the collective interdependence, meaning *C* is high, the more citizens follow their self-interest by seeking hill-climbing opportunities. Such moves eventually lead to negative dynamics on their landscapes in terms of welfare "drops." Their focus on their own interests, often habitual in nature (for example, cooking in an energy inefficient way), leads to a "drop" in citizens' welfare after making such choices (Wood & Newborough, 2003) because of the negative implications of the common pool. In other words, the landscape is "misleading" citizens towards a peak that disappears once citizens have moved there because of the negative dynamics emerging from individualistic hill-climbing on dancing landscapes (Levinthal & Warglien, 1999).

Policy makers in Kansas City benefit from the Smart Grid's IoT infrastructure and smart end-user platform to observe (1) the decision attributes that cause interdependencies between citizens' choices as well as and (2) the degree of negative dynamics caused by such interdependencies. Real-time energy consumption data combined with real-time data from the grid gave them transparency about the high degree of behavioral interdependencies between decision attributes shaped by the policy. For example, they learned that a citizen's behavior of *energy conservation (*no conservation, based on experience or based on smart consumption features), the *timing* of their behavior (off-peak, peak time), the *equipment* they chose to install, and/or their degree of energy *generation* are key attributes that create the negative self-reinforcing dependencies on "dancing" landscapes described above (SmartGrid, 2011). They might also have learned about the negative implications of such dancing landscapes in terms of collective welfare. For example, they might have observed that under conditions where citizens exploit individual benefits (e.g., he/she does not conserve energy on a day-to-day basis, consumes energy during peak times [summer, daytime, using equipment with low-energy efficiency]) when climbing up their individual landscapes, they eventually benefit less individually than they imagined they would (e.g., higher prices during peak times, negative social reputation because of failure to meet social norms).

We will next discuss how policy makers can utilize transparency about such collective interdependencies in order to: (1) tune to reverse the negative dynamics created by such collective interdependencies between citizen landscapes and encourage illusionary local search on dancing landscapes; and (2) nudge citizens into distant moves through social information sharing.

4.5.2. Orchestrating mechanism for illusionary local search via dynamical landscapes tuning

Our modeling effort suggests that policy makers can utilize transparency to reverse the negative self-reinforcing processes created through collective interdependence. To do so, they need to use transparency to support citizens in what Levinthal and Warglien (1999) refer to as *illusionary hill-climbing*. Illusionary hill-climbing can happen if policy makers create a fictional landscape that makes citizens – sitting on their individual landscape at a certain location – perceive a fictional *positive* gradient around them, even though, in reality, such a gradient does not exist prior to the "move." However, once citizens move in that direction, the negative collective interdependencies make the citizens' landscape dance: the real peak rises because of this illusionary move. Such a positive experience, in alignment with the group's goal, reinforces such an illusionary hill-climbing move. One important condition, though, is that such illusionary hill-climbing happens in coordination: If some citizens are unable (or willing) to perceive and act upon an illusionary hill-climbing move, a positive dynamic will not emerge but instead the collective will shift away from a greater collective welfare.

In the Smart Grid Program in Kansas City, policy makers created such an illusionary hill-climbing option: by introducing *smart consumption* as a policy solution, it modified how citizens engage in day-to-day energy conservation actions (Allen, 2011; Wakefield & Hedges, 2010). With smart pricing (real-time, differentiated by appliances), combined with the use of MySmart display (Allen, 2011), real-time and disaggregrated feedback about energy consumption for different activities (heating & cooling, lighting) and appliances can be achieved, thus helping policy makers aim to reverse the negative self-reinforcing mechanism for individualism and self-interest.

By lowering the costs during off-peak times in real time and increasing prices real-time during peaks, citizens shift their attention to opportunities that allow for simple cost reduction in alignment with their tendency to act individualistically because of established habits and routines, e.g., for heating & cooling or lighting. For example, they could see their high costs for cooking during peak times, and use the predictive functions for the next day to adjust their behavior ad-hoc and cook a little earlier. Visibility about positive benefits of such a slight move adjustment (e.g., energy savings, lowering costs) signaled a positive gradient before making such a move. It also led to actual welfare benefits. Smart Grid products and tools gave citizens the ability to manage their energy use, which then helped them save money on their monthly electric bills (Wakefield & Hedges, 2010). Assuming that many people are sensitive to pricing and information feedback, it is "coordinated" illusionary hill-climbing among the citizens as members of the Smart Grid that explains the positive alignment with the policy. By moving downward on their landscapes, the citizens reversed the dynamics from a negative into a positive one. While moving downward, an upward shift of the citizens' peak occurred.

The fact that the project reported a decline in energy consumption, on average, of 10% during peak demand periods (Hedges, 2015), indicates that the policy solution, with smart consumption features being an essential component, was generative in the sense that it triggered positive dynamics potentially afforded through illusionary hill-climbing. It might also explain why policy evaluation reported greater reliability of collective energy provision and reduced outage (Hedges, 2015; Wakefield & Hedges, 2010).

4.5.3. Social learning mechanism for illusionary distant search via information sharing on dancing landscapes

Policy makers may also use transparency about collective interdependencies to encourage citizens to engage in illusionary distant search (Levinthal & Warglien, 1999). Our co-evolutionary modeling suggests that social information can create the illusion of a distant location with a higher peak that aligns well with a visible norm of preserving the common pool of resources (Ostrom, 1990). The social information not only provides some form of a confirmation that social peaks exist but also suggests which decision attributes to change. As mentioned earlier in Section 4.3., such a socially informed distant long-jump is somewhat uncertain as it relates to actions a citizen has not taken before. However, the social information warrants some sort of isolation from a potential risk of unexpectedly high welfare drops. Such guidance is essential to reverse the negative collective interdependencies and encourage citizens to coordinate their actions towards a collective goal in order to utilize the common pool of resources in a socially optimal way.

In the Smart Grid Program in Kansas City, transparency was utilized for such a form of illusionary distant move on dancing landscapes. The Customer Web Portal (also called MySmart portal) was a full-featured informational web portal offering opportunities for “shared learning via experiences from how others use energy more efficiently” (Allen, 2011, p. 16). Citizens could observe the welfare achieved by the community as a whole, i.e., the total kWh consumed per day, the average costs per hour per citizen, the total kWh produced by citizens (in their role as energy producers). Through social information, they potentially also learned about what others were doing to align with this goal, such as buying energy efficient equipment, installing a new solar cell or automation control features for their homes (e.g., a thermostat with pre-sets and a scheduling function). Essentially, the social information framed a collective mindset while also creating a “postcard” map with tips and tricks on how achieve a community goal. While the perceived benefits were only an “illusion” in the first place – since they required individuals to take the effort and install new equipment, purchase new control features, change their day-to-day activities – the benefits became real as soon as the citizens engaged in this new behavior with confidence. The real peak associated with that choice had “risen,” not only because of their own choice but because many others also aligned with the collective goals (Taft & Becker-Dippmann, 2015).

5. Implications for existing literature

In this paper, we asked the question: *What generative mechanisms explain how transparency-enabled policy making enable a civic complex adaptive system (CAS) to evolve towards greater human welfare?* We used conceptual modeling, a methodology accepted and established in public administration literature (e.g. Rhodes Rhodes, 2012; Rhodes & Dowling, 2018), to deeply engage with the general theory of evolutionary adaptation on NK fitness landscapes through formal representation of the key properties of the landscape model as well as empirical analysis of historical data in three distinct policy areas. Our empirically grounded framework summarized in Fig. 3 is the first effort in the public policy literature that rigorously maps an NKC fitness model to the context of transparency in policy making. The results of our complexity modeling, the identification of six generative mechanisms summarized in Table 4, provide new rigorous explanations of how transparency in policy making can lead to more effective and socially desirable outcomes. These insights have implications for two literature streams, namely the literature on digitally-enabled transparency in participatory policy making, as well as the literature on complexity in public policy and public administration. We will comment on both streams in the following section.

5.1. Implications for literature on transparency in participatory policy making

Our results advance the recent discourse on the transformative role of transparency and information sharing in participatory policy making. This literature suggests that platform technologies like social media, IoT, and data analytics, and the transparency afforded through them, transform the overall policy cycle since transparency creates new indirect levers for encouraging behavioral change (Janssen & Helbig, 2016; Janssen & Kuk, 2016; Matheus et al., 2018; Meijer, 2013). Prior literature suggests that these levers unfold through *orchestration* and *nudging*. Our modeling provides a new perspective towards these indirect forms of policy making through a complexity lens.

5.1.1. Orchestration

First, we corroborate recent arguments about the fact that digitally-enabled transparency and data-driven policy making creates new *indirect* roles of orchestration (Janssen & Estevez, 2013; Janssen & Helbig, 2016). The general notion is that orchestration is a process of supervising the discovery, design, and evaluation of policy solutions (Janssen & Helbig, 2016, p.6) rather than the mere provision of solutions by policy makers themselves. Our dynamic theory suggests that such orchestration roles follow principles of co-evolutionary adaptation and self-organization, in which order spontaneously arises from citizens' actions outside of centralized control. Using the powerful concept of a fitness landscape mapped onto a citizen's decision space on which citizens adapt in response to policy makers' actions, we show that the very idea of orchestrating for self-organization is not an oxymoron. We articulate how transparency facilitates policy makers to take new indirect orchestrating roles in the form of what Levinthal and Warglien (1999) refer to as landscape designers, who consider the uniqueness of each citizen's context. Our results, summarized in Table 4, present three different forms of orchestration that explain how transparent policy making enables citizens to adapt in alignment with policy goals.

First, our theory shifts the focus of discovery of the actual policy solution to the observability of citizen as searchers of interdependent landscapes, which represent the interdependent decision spaces that policy makers directly and indirectly change and modify through their policy making actions. Thus, instead of using transparency to source the optimal policy solutions with the greatest predicted welfare impact (Janssen & Helbig, 2016; Linders, 2012), transparency is generative if it facilitates policy makers in uncovering in how citizens make decisions, and how the context of citizens' choices creates uncertainty and ambiguity. In NKC language, this implies that they uncover the properties of the citizen landscapes and how citizens search across it. For example, in the *E*-health Program in VCO, policy makers did use a transparent policy cycle to learn about many interdependencies between the various e-health care-related decision attributes. They learned that such high interdependence created uncertainty, freezing behavioral change (Rhodes, 2012) since they would not know how to combine e-health with their existing healthcare routines. In short, the sources of complexity need to be in focus when discovering policy solutions.

Second, our insights extend prior arguments made about the need for simplification, personalization, and consistency when iteratively (re)-designing and evaluating policy solutions based on insights gathered during the discovery process (Janssen & Kuk, 2016;Linders, 2012; Sunstein, 2014). Our results show that for orchestration to unfold successfully, policy makers use their insights as landscape designers who carefully modify the decision space of the citizens so that it is *consistent* with the idiosyncratic context of the citizens, who are diverse in their context and experiences. Simply speaking, what is made transparent to the citizens should enable them to take advantage of their local knowledge, that is the behaviors they are familiar with (Linders, 2012). Referring back to the E-health Program in VCO, policy makers "tuned" down the interdependencies and ensured that there is greater compatibility between each citizen's particular healthcare service choice and an e-health solution. Through such "tuning" activities, they created a smooth landscape with a visible, single peak that guided citizens towards higher welfare, irrespective of their current position on the landscape. Since the policy makers simplified the decision context, citizens could align easily. For example, they could start monitoring her blood sugar remotely, without having to change other services (e.g., her current outpatient service providers). Indeed, "greater […] transparency do[es] not necessarily improve understanding" (Janssen & Kuk, 2016, p.371). On the contrary, what is observable and communicated to the citizen about her/his policy-related choices – or, in other words, her citizen landscape – matters. If it is consistent with the citizen's particular context (or, in other words, her position in the citizen landscape) it may impact success. As we show with our empirical data, a focus on personalization may lead to greater policy success, even if the underlying policy solutions are not optimally designed from the perspective of economic optimization (Eliasson, 2008). Thus, we suggest that future work on transparency and data-driven policy making should consider that orchestration for self-organization comes in different forms, each considering the unique citizen context. There is a unique orchestrating mechanism that responds to different sources of uncertainty in the citizens' decision context: (1) internal decision interdependence; (2) decision bias; and (3) collective decision interdependence. We hope that future theory development on orchestration in policy making integrates insights from our tri-partite view of transparency and that related orchestration mechanisms.

5.1.2. Nudging and information sharing

Our framework also has implications for the discussion on information sharing and nudging in transparent policy making. According to this discussion, transparency affords policy makers in realizing behavioral levers that "nudge" citizens into socially desirable behavior (EC, 2019; Profir, 2015; Shafir, 2013; Sunstein, 2014). The general argument is that targeted information sharing that "nudges" without restricting the freedom of choice is a powerful form of policy making since it subtly encourages behavioral change. Our framework proposes a co-evolutionary view towards "nudging," with a focus on new forms of social nudging (Linders, 2012; Sunstein, 2014). A social nudge is typically assumed to be the social norm, where insights on what "most of others are doing or thinking" trigger adherence to the status quo. However, a co-evolutionary view towards social nudging goes beyond that. Social media and online collaboration platforms offer new means to iteratively learn across different contexts "by collapsing time, space and hierarchy" (Linders, 2012, p. 450). Our framework suggests that social information may nudge citizens into social learning, during which citizens are not ridiculously credulous but integrate their own experiences and those of diverse others. We identified three forms of social learning, each reflecting the particular nature of three sources of complexity in the citizen's decision space. For example, in the third case on Smart Grid in Kansas City, citizens could observe the collective interdependence among their own and others' choices, since they were notified about the community's energy conservation in real time, as well as the choices of others in consuming and producing energy. Having insights about experiences of others while learning about the implications of the interdependence between their actions for their own personal benefits (e.g., costs of energy consumption) explains why citizens started to make more fundamental changes in their energy behavior inspired by insights from others (e.g., buying energy efficient equipment or installing a solar panel).

5.2. Implications for the literature on complexity in public policy and public administration

Our results have three implications for the stream of complexity literature in public policy and public administration (Schneider Rhodes, 2012), specifically, recent efforts which deeply engage with the fitness landscape model (Gerrits & Marks, 2014) through empirically-grounded modeling rather than just sensitizing metaphorizing (Rhodes & Dowling, 2018) in order to develop new theories of public policy and governance (Rhodes Rhodes, 2012). In particular, our results directly respond to the call made by Rhodes and Dowling (Rhodes, 2008; Rhodes & Dowling, 2018) for more granular efforts in engaging with the properties of the NK fitness landscape (Rhodes, 2008; Rhodes & Dowling, 2018) in order to explain how: (1) *interdependencies* among the agents and their decisions in the CAS (Rhodes & Dowling, 2018) as well as (2) *information dissemination* and *co-ordinational activities* across agents shape the evolutionary adaptation of the agents represented in CAS, or, in other words, its generative (or adaptive) capacity (Schneider Rhodes, 2012).

First, our results bring new insights into existing modeling attempts that point to social *interdependencies among agents and their decisions* in different policy domains, such as anticorruptions (Michael, 2004), education (Toh & So, 2011), and protesters' behavior (Sword, 2007). Such attempts generally conclude the "adaptive moves of agents in search of a better 'fit' have a *reciprocal* influence on other agents" (Gerrits & Marks, 2012), which can cause unexpected co-evolutionary processes that governance theories need to incorporate. They indicate that such interdependence is a critical source of Kauffman's (Kauffman, 1993) complexity catastrophe that may render policy making ineffective. However, as Rhodes and Dowling (2018) highlight, existing modeling efforts concerned with this form of interdependence require more granular modeling. Our results suggest that existing public policy theory using complexity should distinguish between two different types of interdependence, namely individual and collective interdependence, and the adaptive processes emerging from it. Our inquiry into the smart energy policy domain in the Kansas City case suggests that such interdependence, represented as *K* in the NKC fitness landscape model, can cause dynamical processes of adaptation on "dancing, and socially moderated landscapes." Such processes are distinct from the adaptation that is caused by complexity rooted in individual cognitive processes, namely individual decision interdependence and decision bias. By articulating the distinct nature of adaptive processes of fitness landscapes, we respond to the questions raised by Butler and Allen (Butler & Allen, 2008, p.435): "Are [these processes] individual and cognitive, do they take place at the group and organizational levels, or do they take place more dynamically at all levels?"

Second, our modeling of complex CAS in three policy domains also has implications for the discussion on the role of information dissemination and coordination in policy theories geared towards complexity (Rhodes & Dowling, 2018). Existing policy-making theory using fitness landscape modeling concludes that *"information feedback* from the agents' environment" is essential for its generative (or adaptive) capacity of the system to align with a policy goal (Astbury et al., 2009; Gerrits & Marks, 2014) as well as the policy makers' rules created to support their goals (Rhodes Rhodes, 2012). Our unique contribution to this discourse is that we distinguish between different forms of information-based coordination by introducing a *tri-partitive view* of transparency, conceptualized as observability of information related to different three properties of the citizens' fitness landscapes, which policy makers design through their policy-making actions: (1) individual decision interdependence; (2) decision bias; as well as (3) collective decision interdependence. Our empirically grounded framework explains how policy makers can utilize each of these transparencies, so they translate into a generative mechanism, a system-immanent capacity that increases the effectiveness of policy making through interaction with a transparent decision environment (Gerrits & Marks, 2014; Rhodes & Dowling, 2018). Specifically, we extend Rhodes Rhodes' (2012) findings about the implications of *uncertainty* in policy making. On the one hand, we show that transparency can afford an orchestrating mechanism that unfolds via fitness landscape tuning that reduces uncertainty because they tune fitness landscapes in a way that encourages local search, or in other words, affords incremental behavioral change at low levels of uncertainty. We learn that with respect to all three sources of complexity, the reduction of uncertainty through landscape tuning unfolds in a unique way. Complementary to this generative mechanism of "orchestration via fitness landscape tuning," we learn that all three types of transparencies may also create a generative mechanism of "social learning via information sharing" in which citizens become more tolerant to uncertainty. To conclude, both generative mechanisms – orchestration as well as social learning – offer new explanations for how policy making can utilize digitally-enabled transparency for effective policy making by manipulating uncertainty or citizens' tolerance of it.

5.3. Conclusion

Platform technologies – social media, IoT, and data analytics – force a reinterpretation of the role of government as well as the concept of transparency. The rise of platform technologies has the potential to fundamentally change the role of transparency in policy making. Citizens as participants in policy making, who cannot be "controlled" but only be facilitated, move to the center of the discourse on transparency – their challenges, opinions, and responses to policies and policy-related information become observable, interpretable, and sharable. The direction is clear: The discourse has shifted from the question of whether there is a need for transparency to: If and how can transparency be utilized for more indirect levers for behavioral change outside of central control? Contemporary policy practices show that some policy makers have taken up the challenge to realize this potential. However, the lack of robust theoretical foundations has made it difficult to explain how policy making can utilize transparency in a way that equips the citizens with a generative capacity to align with the policy goal while also isolating socially undesirable outcomes with negative implications for human welfare.

This paper has turned to established literature on complexity in public policy and public administration to help to build such theoretical foundations. This stream has recognized that policy making is concerned with complex systems consisting of diverse human agents prone to uncontrollable behavior (Rhodes & Dowling, 2018, p. 997) but has not sufficiently incorporated the role of digitally-enabled transparency. To bring depth to the discourse in both streams, we make one of the first attempts to map Kauffman's (1997) seminal NKC fitness landscape model of co-evolutionary complexity to the phenomenon of transparency in public policy making. This model has been proven to be a generalizable theory to reason about complexity in various empirical settings. Our key assumptions and properties of a citizen fitness landscape model, summarized in Table 3, bring order to the confusion of loose conceptualizations of complexity in hopes that other scholars can replicate our modeling and further advance it. Our framework (Fig. 3) and our key findings on six generative mechanisms (Table 4) build upon these foundations and offer a first version of a theory that explains the effect of digitally-enabled transparency in policy making. It not only offers a granular tri-partite conceptualization of transparency that other scholars may study further. It also articulates, grounded in empirical analysis, the generative mechanisms of: (1) orchestration and (2) social learning that explain the implications for policy outcomes. It is a foundation for other scholars to study these generative mechanisms in further detail, and to compare and contrast the effect of each them. Indeed, future research should bring greater precision to the differential effects of each transparency independently and jointly. This theory is informed by a very recent phenomenon. Future research building upon our findings may update our work. As the empirical phenomenon evolves, new empirical insights should be integrated.

Even though the phenomenon we are studying is young, it has immediate implications for policy practice. On the one hand, policy makers may use our framework to assess the current transparency practice and identify their depth of insights into each of the three sources of complexity in their citizens' decision architecture. On the other hand, they may also evaluate their current ability to utilize such transparency in a generative way, by either focusing their efforts on "tuning" their citizens' choice architecture or by designing social nudges. We hope that future work and practice will align and integrate our framework with the broader policy practice, including the use of appropriate ICT tools, maturity models, and performance metrics so that it can facilitate policy practice more easily.

Acknowledgement

This research would not be possible with constructive feedback and help from others (Erik W. Johnston, Arizone State University). We also would like to thank representatives of the European Commission, the members of the policy advisory group on open innovation and public policy and the team of the World Economic Forum for their constructive feedback. The activities performed in the NSF grant with the number #1462044 inspired and complemented this work. This research has been partly funded by the Social European Fund and the Secretary for Research and Universities of the Department of Economy and Knowledge of Generalitat of Catalonia- FI_B00345

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.giq.2019.05.005.

References

Afuah, A., & Tucci, C. (2012). Crowdsourcing as a solution to distant search. *The Academy of Management Review, 37*(3), 355–375.

Albert, S. M., Shevchik, G. J., Paone, S., & Martich, G. D. (2011). Internet-based medical visit and diagnosis for common medical problems: Experience of first user cohort. *Telemedicine Journal and E-Health, 17*(4), 304–308. https://doi.org/10.1089/tmj.2010.0156.

Allen, G. (2011). *KCP&L SmartGrid demonstration APPA facilities drive in workshop.* 84.

Allison, G. T. (1971). Essence of decision : Explaining the Cuban missile crisis. Retrieved from https://trove.nla.gov.au/work/8773193.

Almirall, E., & Casadesus-Masanell, R. (2010). Open versus closed innovation: A model of discovery and divergence. *Academy of management review, 35*(1), 27–47.

Anderson, P. (1999). Perspective: Complexity theory and organization science. *Organization Science, 10*(3), 216–232.

Astbury, J., Huddart, S., & Théoret, P. (2009). Making the path as we walk it: Changing context and strategy on green street. *Canadian Journal of Environmental Education (CJEE), 14*(0), 158–178.

Attard, J., Orlandi, F., Scerri, S., & Auer, S. (2015). A systematic review of open government data initiatives. *Government Information Quarterly, 32*(4), 399–418. https://doi.org/10.1016/j.giq.2015.07.006.

Avineri, E. (2012). On the use and potential of behavioural economics from the perspective of transport and climate change. *Journal of Transport Geography, 24*, 512–521. https://doi.org/10.1016/j.jtrangeo.2012.03.003.

Bandura, A. (1965). Vicarious processes: A case of no-trial Learning1. In B. Leonard (Vol. Ed.), *Advances in experimental social psychology. Vol. 2. Advances in experimental social psychology* (pp. 1–55). Academic Press.

Benkler, Y. (2006). *The wealth of networks: How social production transforms markets and freedom.* Yale University Press.

Bergmann, G. (1957). *Philosophy of science.* Madison, WI, US: University of Wisconsin Press.

Bertot, J. C., Jaeger, P. T., & Grimes, J. M. (2010). Using ICTs to create a culture of transparency: E-government and social media as openness and anti-corruption tools for societies. *Government Information Quarterly, 27*(3), 264–271. https://doi.org/10.1016/j.giq.2010.03.001.

Billinger, S., Stieglitz, N., & Schumacher, T. R. (2014). Search on rugged landscapes: An experimental study. *Organization Science, 25*(1), 93–108. https://doi.org/10.1287/orsc.2013.0829.

Börjesson, M., Eliasson, J., & Franklin, J. P. (2012). Valuations of travel time variability in scheduling versus mean–variance models. *Transportation Research Part B: Methodological, 46*(7), 855–873. https://doi.org/10.1016/j.trb.2012.02.004.

Börjesson, M., Eliasson, J., Hugosson, M. B., & Brundell-Freij, K. (2012). The Stockholm congestion charges—5 years on. Effects, acceptability and lessons learnt. *Transport Policy, 20*, 1–12. https://doi.org/10.1016/j.tranpol.2011.11.001.

Brewer, G. D., & DeLeon, P. (1983). *The foundations of policy analysis.* Brooks/Cole Publishing.

Brunswicker, S., Almirall, E., & Majchrzak, A. (2019). Optimizing and satisficing: The interplay between platform architecture and Developers' Design strategies on platform performance. *Management information systems quarterly* (forthcoming).

Butler, M. J. R., & Allen, P. M. (2008). Understanding policy implementation processes as self-organizing systems. *Public Management Review, 10*(3), 421–440. https://doi.org/10.1080/14719030802002923.

Central European Living Lab for Territorial Innovation (2019). Retrieved May 16, 2018, from http://centralivinglab.eu/index.php/en/pilots/ehealth.

Davis, J. P., Eisenhardt, K. M., & Bingham, C. B. (2007). Developing theory through simulation methods. *Academy of Management Review, 32*(2), 480–499.

Davis, J. P., Eisenhardt, K. M., & Bingham, C. B. (2009). Optimal structure, market dynamism, and the strategy of simple rules. *Administrative Science Quarterly, 54*(3), 413–452.

Dawes, S. S. (2010). Stewardship and usefulness: Policy principles for information-based transparency. *Government Information Quarterly, 27*(4), 377–383. https://doi.org/10.1016/j.giq.2010.07.001.

Dawes, S. S., & Helbig, N. (2010). Information strategies for open government: Challenges and prospects for deriving public value from government transparency. In M. A. Wimmer, J.-L. Chappelet, M. Janssen, & H. J. Scholl (Eds.). *Electronic government* (pp. 50–60). Berlin Heidelberg: Springer.

Dunleavy, P., Margetts, H., Bastow, S., & Tinkler, J. (2006). New public management is dead—Long live digital-era governance. *Journal of Public Administration Research and Theory, 16*(3), 467–494. https://doi.org/10.1093/jopart/mui057.

Eliasson, J. (2012). How to solve traffic jams. TedxHelvetia Retrieved from website: http://www.ted.com/talks/jonas eliasson how to solve traffic jams.html.

Eliasson, J. (2008). Lessons from the Stockholm congestion charging trial. *Transport Policy, 15*(6), 395–404. https://doi.org/10.1016/j.tranpol.2008.12.004.

Eliasson, J. (2009). A cost–benefit analysis of the Stockholm congestion charging system. *Transportation Research Part A: Policy and Practice, 43*(4), 468–480. https://doi.org/10.1016/j.tra.2008.11.014.

Eliasson, J. (2014). *The Stockholm congestion charges: An overview.* (Working Paper, 42).

Eliasson, J., Hultkrantz, L., Nerhagen, L., & Rosqvist, L. S. (2009). The Stockholm congestion – Charging trial 2006: Overview of effects. *Transportation Research Part A: Policy and Practice, 43*(3), 240–250. https://doi.org/10.1016/j.tra.2008.09.007.

Eliasson, J., & Jonsson, L. (2011). The unexpected "yes": Explanatory factors behind the positive attitudes to congestion charges in Stockholm. *Transport Policy, 18*(4), 636–647. https://doi.org/10.1016/j.tranpol.2011.03.006.

Eppel, E. (2012). The application of a complexity analytical lens to explain and understand public policy processes. *Compact I: Public administration in complexity*. Emergent Publication.

Eppel, E. A., & Rhodes, M. L. (2018). Complexity theory and public management: A 'becoming' field. *Public Management Review, 20*(7), 949–959. https://doi.org/10.1080/14719037.2017.1364414.

European Comission (2019). About the policy lab. Retrieved April 6, 2019, from https://blogs.ec.europa.eu/eupolicylab/about-us/.

Ferro, E., Loukis, E. N., Charalabidis, Y., & Osella, M. (2013). Policy making 2.0: From theory to practice. *Government Information Quarterly, 30*(4), 359–368. https://doi.org/10.1016/j.giq.2013.05.018.

Frenken, K. (2006). A fitness landscape approach to technological complexity, modularity, and vertical disintegration. *Structural Change and Economic Dynamics, 17*(3), 288–305. https://doi.org/10.1016/j.strueco.2006.01.001.

Gavetti, G., & Warglien, M. (2015). A model of collective interpretation. *Organization Science, 26*(5), 1263–1283. https://doi.org/10.1287/orsc.2015.0987.

Gell-Mann, M. (1995). *The quark and the jaguar: Adventures in the simple and the complex.* Macmillan.

Gerrits, L., & Marks, P. (Eds.). (2012). *COMPACT I: Public administration in complexity*. ISCE Publishing.

Gerrits, L., & Marks, P. (2014). The interpretations and uses of fitness landscapes in the social sciences. Retrieved from https://repub.eur.nl/pub/51659/.

Geyer, R., & Pickering, S. (2011). Applying the tools of complexity to the international realm: From fitness landscapes to complexity cascades. *Cambridge Review of International Affairs, 24*(1), 5–26. https://doi.org/10.1080/09557571.2011.558053.

Gigerenzer, G., & Todd, P. M. (1999). *Simple heuristics that make us smart.* USA: Oxford University Press.

Glance, N. S., & Huberman, B. A. (1994). The dynamics of social dilemmas. *Scientific American, 270*(3), 76–81.

Goulden, M., Bedwell, B., Rennick-Egglestone, S., Rodden, T., & Spence, A. (2014). Smart grids, smart users? The role of the user in demand side management. *Energy Research & Social Science, 2*, 21–29. https://doi.org/10.1016/j.erss.2014.04.008.

Harrison, T. M., & Sayogo, D. S. (2014). Transparency, participation, and accountability practices in open government: A comparative study. *Government Information Quarterly, 31*(4), 513–525. https://doi.org/10.1016/j.giq.2014.08.002.

Head, B. W., & Alford, J. (2015). Wicked problems: Implications for public policy and management. *Administration & Society, 47*(6), 711–739. https://doi.org/10.1177/0095399713481601.

Hedges, E. T. (2015). *Recovery act-SmartGrid regional demonstration transmission and distribution (T&D) infrastructure.* https://doi.org/10.2172/1223441.

Hills, T. T., Todd, P. M., Lazer, D., Redish, A. D., & Couzin, I. D. (2015). Exploration versus exploitation in space, mind, and society. *Trends in Cognitive Sciences, 19*(1), 46–54. https://doi.org/10.1016/j.tics.2014.10.004.

Holland, J. H. (1992). Complex adaptive systems. *Daedalus, 121*(1), 17–30.

Holland, J. H., & Miller, J. H. (1991). Artificial adaptive agents in economic theory. *The American Economic Review, 81*(2), 365–370.

Hurwicz, L. (1973). *The Design of Mechanisms for resource allocation.* 34.

Jaeger, P. T., & Bertot, J. C. (2010). Transparency and technological change: Ensuring equal and sustained public access to government information. *Government Information Quarterly, 27*(4), 371–376. https://doi.org/10.1016/j.giq.2010.05.003.

Janssen, M., & Estevez, E. (2013). Lean government and platform-based governance—Doing more with less. *Government Information Quarterly, 30*, S1–S8. https://doi.org/10.1016/j.giq.2012.11.003.

Janssen, M., & Helbig, N. (2016). Innovating and changing the policy-cycle: Policy-makers be prepared!. *Government Information Quarterly*. https://doi.org/10.1016/j.giq.2015.11.009.

Janssen, M., & Kuk, G. (2016). The challenges and limits of big data algorithms in technocratic governance. *Government Information Quarterly, 33*(3), 371–377. https://doi.org/10.1016/j.giq.2016.08.011.

Kahneman, D. (2003). Maps of bounded rationality: Psychology for Behavioral economics. *The American Economic Review, 93*(5), 1449–1475.

Karlström, A., & Franklin, J. P. (2009). Behavioral adjustments and equity effects of congestion pricing: Analysis of morning commutes during the Stockholm Trial. *Transportation Research Part A: Policy and Practice, 43*(3), 283–296. https://doi.org/10.1016/j.tra.2008.09.008.

Kauffman, S. (1993). *The origins of order: Self-organization and selection in evolution.* Oxford University Press.

Kauffman, S. (1995). *At home in the universe.* London: Penguin Books.

Kauffman, S., & Levin, S. (1987). Towards a general theory of adaptive walks on rugged landscapes. *Journal of Theoretical Biology, 128*(1), 11–45. https://doi.org/10.1016/S0022-5193(87)80029-2.

Klijn, E.-H. (2008). Complexity theory and public administration: What's new? *Public Management Review, 10*(3), 299–317. https://doi.org/10.1080/14719030802002675.

Koput, K. W. (1997). A chaotic model of innovative search: some answers, many questions. *Organization Science, 8*(5), 528–542.

Lathrop, D., & Ruma, L. (2010). *Open government: Collaboration, transparency, and participation in practice.* O'Reilly Media, Inc.

Lee, H., Tsohou, A., & Choi, Y. (2017). Embedding persuasive features into policy issues: Implications to designing public participation processes. *Government Information Quarterly, 34*(4), 591–600. https://doi.org/10.1016/j.giq.2017.11.006.

Levinthal, D., & March, J. G. (1981). A model of adaptive organizational search. *Journal of Economic Behavior & Organization, 2*(4), 307–333. https://doi.org/10.1016/0167-2681(81)90012-3.

Levinthal, D. A. (1997). Adaptation on rugged landscapes. *Management Science, 43*(7), 934–950 (Retrieved from JSTOR).

Levinthal, D. A., & Warglien, M. (1999). Landscape design: Designing for local action in complex worlds. *Organization Science, 10*(3), 342–357.

Levitan, B., Lobo, J., Schuler, R., & Kauffman, S. (2002). Evolution of organizational performance and stability in a stochastic environment. *Computational & Mathematical Organization Theory, 8*(4), 281–313.

Lin, Z. J., Kitts, J. A., Yang, H., & Harrison, J. R. (2008). Elucidating strategic network dynamics through computational modeling. *Computational and Mathematical Organization Theory, 14*(3), 175–208.

Lindblom, C. E., & Cohen, D. K. (1979). *Usable knowledge: Social science and social problem solving.* Yale University Press.

Linders, D. (2012). From e-government to we-government: Defining a typology for citizen coproduction in the age of social media. *Government Information Quarterly, 29*(4), 446–454. https://doi.org/10.1016/j.giq.2012.06.003.

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science, 2*(1), 71–87. https://doi.org/10.1287/orsc.2.1.71.

March, J. G., & Simon, H. A. (1958). Organizations (SSRN scholarly Paper No. ID 1496194). Retrieved from Social Science Research Network website: https://papers.ssrn.com/abstract=1496194.

Marks, P., Gerrits, L., & Marx, J. (2019). How to use fitness landscape models for the analysis of collective decision-making: A case of theory-transfer and its limitations. *Biology and Philosophy, 34*(1), 7. https://doi.org/10.1007/s10539-018-9669-4.

Maskin, E. S. (2008). Mechanism design: How to implement social goals. *American Economic Review, 98*(3), 567–576. https://doi.org/10.1257/aer.98.3.567.

Matheus, R., Janssen, M., & Maheshwari, D. (2018). Data science empowering the public: Data-driven dashboards for transparent and accountable decision-making in smart cities. *Government Information Quarterly*. https://doi.org/10.1016/j.giq.2018.01.006.

McKelvey, B. (1999). Avoiding complexity catastrophe in Coevolutionary pockets: Strategies for rugged landscapes. *Organization Science, 10*, 294–321.

Medaglia, R. (2012). eParticipation research: Moving characterization forward (2006–2011). *Government Information Quarterly, 29*(3), 346–360. https://doi.org/10.1016/j.giq.2012.02.010.

Meijer, A. (2013). Understanding the complex dynamics of transparency. *Public Administration Review, 73*(3), 429–439. https://doi.org/10.1111/puar.12032.

Michael, B. (2004). Explaining organizational change in international development: The role of complexity in anti-corruption work. *Journal of International Development, 16*(8), 1067–1088. https://doi.org/10.1002/jid.1126.

Misuraca, G., Codagnone, C., & Rossel, P. (2013). From practice to theory and back to practice: Reflexivity in measurement and evaluation for evidence-based policy making in the information society. *Government Information Quarterly, 30*(Supplement 1), S68–S82. https://doi.org/10.1016/j.giq.2012.07.011.

Misuraca, G., Rossel, P., & Codagnone, C. (2011). *Foresight and policy modelling on ICT for governance: Exploring the next frontiers. Vol. 217*.

Nam, T. (2012). Suggesting frameworks of citizen-sourcing via Government 2.0. *Government Information Quarterly, 29*(1), 12–20. https://doi.org/10.1016/j.giq.2011.07.005.

Noveck, B. S. (2015). *Smart citizens, smarter state: The Technologies of Expertise and the future of governing.* Harvard University Press.

Nunes, S. C. (2013). *Citizen E-participation in urban governance: Crowdsourcing and collaborative creativity: Crowdsourcing and collaborative creativity.* IGI Global.

Ostrom, E. (1990). *Governing the commons: The evolution of institutions for collective action.* Oxford University Press.

Ostrom, E. (1996). Crossing the great divide: Coproduction, synergy, and development. *World Development, 24*(6), 1073–1087. https://doi.org/10.1016/0305-750X(96)00023-X.

Pillon, S. (2015). *Using Telemedicine to manage the wound care service in the italian public health care system.* 49. Retrieved from https://www.kingsfund.org.uk/sites/default/files/media/T3D_Sergio_Pillon.pdf.

Profir, I. (May 6, 2015). Behavioural insights [text]. Retrieved April 5, 2019, from EU Science Hub - European Commission website https://ec.europa.eu/jrc/en/research/crosscutting-activities/behavioural-insights.

Rellihan, M. (2012). Adaptationism and adaptive thinking in evolutionary psychology. *Philosophical Psychology, 25*(2), 245–277. https://doi.org/10.1080/09515089.2011.579416.

Rendell, L., Fogarty, L., Hoppitt, W. J. E., Morgan, T. J. H., Webster, M. M., & Laland, K. N. (2011). Cognitive culture: Theoretical and empirical insights into social learning strategies. *Trends in Cognitive Sciences, 15*(2), 68–76. https://doi.org/10.1016/j.tics.2010.12.002.

Rhodes, M. L. (2008). Complexity and emergence in public management. *Public Management Review, 10*(3), 361–379. https://doi.org/10.1080/14719030802002717.

Rhodes, M. L. (2012). Advancing public service governance theory using a performance landscape model. *Compact 1: Public administration in complexity* (pp. 225). ISCE Publishing.

Rhodes, M. L., & Dowling, C. (2018). What insights do fitness landscape models provide for theory and practice in public administration? *Public Management Review, 20*(7), 997–1012. https://doi.org/10.1080/14719037.2017.1364412.

Rivkin, J. W., & Siggelkow, N. (2007). Patterned interactions in complex systems: Implications for exploration. *Management Science, 53*(7), 1068–1085. https://doi.org/10.1287/mnsc.1060.0626.

Rojas, L. (2014). Open data and big data: A perspective from Colombia|SpringerLink. Retrieved July 28, 2018, from https://link-springer-com.proxy.library.georgetown.edu/chapter/10.1007/978-3-319-08618-7_4.

Ross, J., Stevenson, F., Lau, R., & Murray, E. (2016). Factors that influence the implementation of e-health: A systematic review of systematic reviews (an update). *Implementation Science: IS, 11*. https://doi.org/10.1186/s13012-016-0510-7.

Rota, A., & Santafede, F. (2012). *La telemedicina per pazienti BPCO e comorbilità limit e potenzialità*.

Sæbø, Ø., Rose, J., & Skiftenes Flak, L. (2008). The shape of eParticipation: Characterizing an emerging research area. *Government Information Quarterly, 25*(3), 400–428. https://doi.org/10.1016/j.giq.2007.04.007.

Schneider, V. (2012). Governance and complexity. *The Oxford handbook of governance*. Retrieved from http://www.oxfordhandbooks.com/view/10.1093/oxfordhb/9780199560530.001.0001/oxfordhb-9780199560530-e-9.

Shafir, E. (2013). *The behavioral foundations of public policy.* Princeton University Press.

Simon, H. A. (1990). Invariants of human behavior. *Annual Review of Psychology, 1–19*(18331187), 41.

Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics, 69*(1), 99–118. https://doi.org/10.2307/1884852.

Simon, H. A. (1973). Organizational man: Rational or self-actualizing? *Public Administration Review, 33*, 346.

Simon, H. A. (1991). Bounded rationality and organizational learning. *Organization Science, 2*(1), 125–134.

Sloman, S., & Fernbach, P. (2018). Reasoning as collaboration. *The American Journal of Psychology, 131*(4), 493–496. https://doi.org/10.5406/amerjpsyc.131.4.0493.

SmartGrid (2011). *Kansas City smart grid*.

Spiliotopoulou, L., & Charalabidis, Y. (2016). Web 2.0 in governance. A framework of utilizing social media and opinion mining methods and tools for policy deliberation. *Information science reference. Social media and networking: Concepts, methodologies, tools, and applications* (pp. 281–303). IGI Global.

Stake, R. (1995). *The art of case study research.* SAGE Publications. Retrieved from https://uk.sagepub.com/en-gb/eur/the-art-of-case-study-research/book4954.

Sunstein, C. R. (2014). Nudging: A very short guide. *Journal of Consumer Policy, 37*(4), 583–588. https://doi.org/10.1007/s10603-014-9273-1.

Susha, I., & Grönlund, Å. (2012). eParticipation research: Systematizing the field. *Government Information Quarterly, 29*(3), 373–382. https://doi.org/10.1016/j.giq.2011.11.005.

Sword, L. D. (2007). Complexity science conflict analysis of power and protest. *Emergence: Complexity and Organization; Mansfield, 9*(3), 47–61.

Taft, J. D., & Becker-Dippmann, A. S. (2015). *The emerging interdependence of the Electric Power Grid & Information and communication technology (No. PNNL–24643, 1221500).* https://doi.org/10.2172/1221500.

Teisman, G. R., & Klijn, E.-H. (2008). Complexity theory and public management. *Public Management Review, 10*(3), 287–297. https://doi.org/10.1080/14719030802002451.

Tennant, B., Stellefson, M., Dodd, V., Chaney, B., Chaney, D., Paige, S., & Alber, J. (2015). eHealth literacy and Web 2.0 Health information seeking Behaviors among baby boomers and older adults. *Journal of Medical Internet Research, 17*(3), https://doi.org/10.2196/jmir.3992.

Thaler, R. H., & Sunsteing, Cass R. (2009). Nudge: Improving decisions about health, wealth, and happiness. Retrieved from https://wrlc-gu.primo.exlibrisgroup.com/discovery/fulldisplay?docid = alma9976185753604108&context = L&vid = 01WRLC_GUNIV:01WRLC_GUNIV&lang = en&search_scope = DN_and_CI&adaptor = Local%20Search%20Engine&isFrbr = true&tab = Everything&query = any,contains,Thaler,%20R.,%20&sortby = date_d&facet = frbrgroupid,include,9040772131447447015&offset = 0.

Toh, Y., & So, H.-J. (2011). ICT reform initiatives in Singapore schools: A complexity theory perspective. *Asia Pacific Education Review, 12*(3), 349–357. https://doi.org/10.1007/s12564-010-9130-0.

Tversky, A., & Kahneman, D. (1986). Rational choice and the framing of decisions. *The Journal of Business, 59*(4), 251–278.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124.

Vojdani, A. (2008). Smart integration. *IEEE Power and Energy Magazine, 6*(6), 71–79. https://doi.org/10.1109/MPE.2008.929744.

Wakefield, M., & Hedges, E. T. (2010). *Kansas City Power & Light Smart Grid Demonstration Project (p. 2).* Electric Power Research Institute.

Weerakkody, V., Janssen, M., & Dwivedi, Y. K. (2011). Transformational change and business process reengineering (BPR): Lessons from the British and Dutch public sector. *Government Information Quarterly, 28*(3), 320–328. https://doi.org/10.1016/j.giq.2010.07.010.

Wolsink, M. (2012). The research agenda on social acceptance of distributed generation in smart grids: Renewable as common pool resources. *Renewable and Sustainable Energy Reviews, 16*(1), 822–835. https://doi.org/10.1016/j.rser.2011.09.006.

Wood, G., & Newborough, M. (2003). Dynamic energy-consumption indicators for domestic appliances: Environment, behaviour and design. *Energy and Buildings, 35*(8), 821–841. https://doi.org/10.1016/S0378-7788(02)00241-4.

Wright, S. (1932). The roles of mutation, inbreeding, crossbreeding and selection in evolution. *Presented at the proceedings of the sixth international congress on genetics*.

Zhang, J., Liu, H., Sayogo, D. S., Picazo-Vela, S., & Luna-Reyes, L. (2016). Strengthening institutional-based trust for sustainable consumption: Lessons for smart disclosure. *Government Information Quarterly, 33*(3), 552–561. https://doi.org/10.1016/j.giq.2016.01.009.

Sabine Brunswicker is an Associate Professor of Digital innovation and Director of the Research Center for Open Digital Innovation at Purdue University. She is an interdisciplinary scholar and a computational social scientist who studies socio-technical research topics with a focus on complexity. Her general research interests lie in understanding the phenomenon of open digital innovation - new digitally-enabled complex socio-technical systems - ranging from open source software, open data, crowdsourcing, digital platforms, blockchains, and human-AI interaction. In 2016, she and her team launched Purdue IronHacks, a unique virtual multi-staged open data competition, in which participants develop apps to solve societal challenges. She is also a policy advisor in the area of digital innovation and open science. Her work has been published in academic journals in the area of innovation, information systems, and computing, and is also featured in business press and media.

Laia Pujol Priego is PhD candidate at ESADE Business School (Universitat Ramon Llull) and a visiting researcher at McDonough Business School at Georgetown University (2017–2018). Previous to start the PhD, Laia worked for twelve years on the design and implementation of digital innovation policies for governments at regional and international level. Her research interests lie in understanding the dynamics of open digital innovation and how the disruption of technological changes in the way of doing and sharing science (e.g open data, digital platforms, open hardware) is impacting innovation ecosystems.

Esteve Almirall is a lecturer in the Department of Information Systems Management and URL Contracted Doctoral Professor. He studies the intersection between technology and innovation and how IT is changing the way we innovate: from the individual inventor to ecosystems, from owing and buying innovations to benefiting from innovations created by others by aligning incentives and motivations.