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Artificial intelligence, institutions, and resilience: Prospects and provocations for cities

Laurie A. Schintler *, Connie L. McNeely

George Mason University, USA

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ABSTRACT

The notion of "smart city" incorporates promises of urban resilience, referring generally to capacities for cities to anticipate, absorb, react, respond, and reorganize in the face of disruptive changes and disturbances. As such, artificial intelligence (AI), coupled with big data, is being heralded as a means for enhancing and accessing key determinants of resilience. At the same time, while AI generally has been extolled for contributions to urban resilience, less attention has been paid to the other side of the equation — i.e., to the ethical, governance, and social downsides of AI and big data that can operate to hinder or compromise resilience. With particular attention to relevant institutional dynamics and features, an encompassing and systemic conception of smart and resilient cities is delineated as a critical lens for viewing and analyzing complex instrumental and intrinsic aspects of the relationship between AI and resilience. As a broader contribution to the literature, a set of structural, process, and outcome conditions are offered for engaging and assessing linkages inherent in the use of AI relative to urban resilience in terms of absorptive capacity, speed of recovery, over-optimization avoidance, and creative destruction, especially as regards impacts on relevant practices, standards, and policies.

1. Introduction

Cities are subject to myriad chronic stresses and acute shocks, including recurring natural and man-made perturbations, such as pandemics, natural disasters, terror attacks, civil wars, industrial accidents, public uprisings, and cyber incidents. Compounding matters, the frequency, intensity, and complexity of extreme events have increased in recent years, particularly as a result of rapid urbanization, globalization, climate change, and political polarization (Eraydin, 2013). Such issues contribute to greater "uncertainty and dramatic change at all socio-economic and spatial scales," including within and across cities (Reggiani et al., 2021). Indeed, effects on urban areas have been of particular concern regarding these kinds of disturbances, especially considering the vital roles that they play in regions as well as the global arena (Glaeser et al., 2020), including as key determinants of individual and community wellbeing (Vlahov & Galea, 2002).

The need to make cities more resilient in the face of continual and intensifying turbulence and uncertainty is a global priority and a grand challenge of this century (DesRoches & Taylor, 2018).[1] Resilience — referring in a general sense to the capacity of a system to adapt or absorb change and disturbance, maintaining its constitutive elements and relationships (cf. Holling, 1973) — is key to achieving long-term sustainability in urban systems and ultimately for ensuring quality of life for both present and future generations

* Corresponding author.
E-mail addresses: lschintl@gmu.edu (L.A. Schintler), cmcneely@gmu.edu (C.L. McNeely).

[1] https://www.un.org/sustainabledevelopment/cities.

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(Romero-Lankao et al., 2016). Indeed, cities cannot effectively function economically, socially, or politically without being resilient. Accordingly, there is growing attention to urban resilience (Reggiani et al., 2021) — and an increase in "resilience thinking" more generally (Folke et al., 2021) — including as applied to “smart” cities.

In this regard, artificial intelligence (AI), comprising a constellation of techniques and technologies working together with big data “to enable machines to sense, comprehend, act, and learn with human-like levels of intelligence,”[2] is seen as a means to promote urban robustness and resilience (Yigitcanlar et al., 2020). In fact, "crisis analytics" is a burgeoning field that leverages AI-based solutions for managing all stages of the "crisis lifecycle" — from mitigation and preparedness to response and recovery (Qadir et al., 2016). Along these same lines, there are a growing number of studies that highlight how AI can enable cities to quickly and efficiently respond to disasters and crises — i.e., to absorb shocks and maintain continuity of operations, and also to anticipate and prevent disruptions in the first place (Sharifi et al., 2021; Sun et al., 2020; Bragazzi et al., 2020; Munawar et al., 2022).

However, little attention has been paid to the other side of the coin: how AI can compromise efforts to maintain, enhance, and build resilient cities (Galaz et al., 2021; Vinuesa et al., 2020; Yigitcanlar et al., 2020). Indeed, technology is always a double-edged sword (Orlikowski, 1992), and, more often than not, the problems it creates are far worse than the ones it intends to fix (Ellul, 1964). The use of AI in particular comes part and parcel with an array of social and ethical risks and dangers, such as algorithmic bias and discrimination, violations of privacy, the disintegration of social connections, and safety hazards (Leslie, 2019). AI systems also tend to be opaque, thus raising additional concerns about transparency and accountability.

Additionally, discussions about the benefits of AI to cities are often narrowly framed through a technocratic lens (Yu et al., 2018), considering mainly engineering and operational issues related to efficiency such as speed of recovery and shock absorption (Santos et al., 2021; Yu et al., 2018). The broader social and institutional complexities and dynamics in which technology is developed, used, and positioned have been largely neglected (Arafah and Winarso, 2017). The deployment of AI in cities creates different connections between humans, machines, and the environment, a situation that is contributing to unprecedented risks and vulnerabilities, which can hinder the path to resilience (Galaz et al., 2021). That is, AI can detract from the resilience capabilities and efforts of cities, especially in the absence of appropriate governance strategies and institutional arrangements (Galaz et al., 2021; Sharifi et al., 2021). This issue is of particular concern for cities that are increasingly smart and dependent on AI by definition.

To garner a fuller and more analytically encompassing understanding of resilience in reference to smart cities, we examine related mechanisms by which AI affects urban resilience. To that end, a brief discussion of relevant theoretical and conceptual dimensions is next offered, with particular attention to technology and governance issues in relation to resilience, as background for a more focused account and delineation of relevant analytical matters. Building on this foundation, the following sections turn on four principal dimensions of resilience: absorptive capacity, speed of recovery, over-optimization avoidance, and creative destruction (Ostrom, 2009). These topics represent major definitional and constituent issues in reference to resilience and are employed here as analytical levers for developing a more in-depth and specific appreciation of resilience in application to the urban context. We engage these dimensions to delineate further determinant relationships and structures whereby AI is addressed relative to urban resilience, considering implications and challenges for smart city governance and planning. The concluding section provides a critical reflection and summary of the main points addressed in the analysis while drawing out implications for a programmatic research agenda and framing questions of resilience relative to broader policy issues. An important contribution of this work is the development of a comprehensive framework that incorporates and lays out the institutionally derived parameters and relationships that define the role of socio-spatio-technological contextual factors and dynamics for examining smart city resilience. This approach requires looking beyond the typical economic and technological deterministic features that mark most discussions of AI in contemporary urban settings. As such, the analysis here contributes to a much needed broader and more in-depth comprehension of the relationship between AI and resilience in general, which stands as an important priority for research and policy (Vineusa et al., 2020).

2. Theoretical and conceptual background

In conceptual terms, resilience has been fraught with ambiguity, reflecting a variety of definitions for research relative to application and disciplinary foci (Irani & Rahnamayiezekavat, 2021). However, while acknowledging this situation, we do not engage the conceptual debates surrounding the term as such but instead draw from them to inform and consider broader implications for smart city interactions, structures, and dynamics. In any case, we can say that, broadly speaking, resilience refers to the capacity of a system to absorb or adapt to change and perturbations. While some approaches emphasize the ability to return to an original situation or state after a disturbance (as in engineering and economics), resilience is not only an outcome or event. Rather, it is a process, and it does not necessarily lead to replication or reproduction in the pure sense; resilience also can involve structural and operational responses and adaptability and a capacity for learning to make improvements and corrections over time (Adger, 2000; Simmie & Martin, 2010; Holling, 1973; Davoudi & Porter, 2012). Note that, as a process, resilience operates under undesirable conditions — risk exposure and disturbances — across definitions and frames of references, but with positive connotations related to bringing the situation to recovery, resistance to instability, or progress (Irani & Rahnamayiezekavat, 2021; Dissart, 2003).

“Urban resilience” in particular refers to adaptation and related capabilities in cities as complex systems (Batty, 2008). As such, calling for an overarching systemic perspective, urban resilience is the ability of cities to withstand change, rebuild after change, and create new structures, typically referencing the “urban ecosystem” and capacities to maintain system functions after a disturbance (Alberti et al., 2003; Norris et al., 2008; Chelleri, 2012; Irani & Rahnamayiezekavat, 2021). In this vein, resilient systems must be

[2] https://www.accenture.com/us-en/insights/artificial-intelligence-summary-index.

flexible and robust at the same time, and resilience itself represents an important benchmark for smart city planning and performance (Santos et al., 2021; Arafah and Winarso, 2017).

Against this backdrop, institutions offer an especially relevant angle for understanding resilience and smart cities. To that end, we adopt an overarching sociological institutionalist perspective in which institutions refer to both the formal and informal rules that underlie and shape the behaviors, practices, and interactions that characterize the relationships and processes in question, and in which institutional capacity is a determinant aspect of urban resilience. From this standpoint, the rules that constitute institutions give collective meaning and value to particular actors and activities, integrating them into larger systems invoking both instrumental and intrinsic characteristics and dynamics (cf. McNeely, 2012; Drori et al., 2003; Meyer et al., 1987; Powell and DiMaggio 1991). More to the point, individuals, organizations, and machines are embedded in an institutional context that dynamically frames and affects their structures and practices. Accordingly, investigation is needed in terms of institutional dynamics and conditions of technological resources and effects to better understand when, where, why, and how resilience leads to robust and adaptive outcomes and effects.

Based on institutionalist arguments, we consider urban resilience as a process relative to systemic interactions affected by and affecting AI as central to conceptions of the smart city. In particular, given varying institutional structures and dynamics attending resilience processes (Rodríguez-Pose, 2013), critical relationships and implications are explored for a finer-grained understanding of AI vis-à-vis relevant capacities. AI itself is concerned with both understanding and building "intelligent" entities that think and act, emphasizing in particular machines that can compute how to perform effectively in a wide variety of situations (Russell & Norvig, 2021). This is obviously a crucial issue in terms of resilience capabilities. AI systems are generally depicted relative to technological expressions and enactments bound by science, engineering, and mathematics, encompassing "logic, probability, and continuous mathematics; perception, reasoning, learning, and action; fairness, trust, social good, and safety; and applications that range from microelectronic devices to robotic planetary explorers to online services with billions of users" (Russell & Norvig, 2021, p. vii). Consequently, AI technology is part of the institutional apparatus of modern society and the smart city.

2.1. Technology and resilience

In a fundamental sense, we can say that technology is about manipulating nature, involving means by which humans change their environments or try to exceed their natural capacities (Volti, 2017). While there are variations on the theme, two broad perspectives have been engaged in conceptualizing technology in general: instrumental and intrinsic. The intrinsic approach refers to issues such as values, beliefs, and attitudes, whereas the instrumental approach implies more functional behavior. Expressed otherwise, technology has been interpreted as a neutral instrument for humans to use for positive change rather than as a value-laden object of control (Orlikowski, 1992), referencing technology as an exogenous versus an endogenous feature of a system. Along these lines, there are a number of debates over whether to consider technology in the intrinsic sense as something of an agent or actor in its own right as opposed to principally playing an instrumental role in affecting society. We consider it in broad terms from both viewpoints relative to urban resilience. However, in connection to urban resilience, instrumental slants on technology have been the most prevalent in the smart city literature. For example, engineering orientations emphasize the ability of an urban system to bounce back quickly from disturbances and absorb shocks without significant loss of functionality (Sharfi et al., 2021). The principal focus is on "efficiency, constancy, and predictability, all attributes at the core of the engineer's desires for a fail-safe design," stressing a quick and efficient return to the pre-disturbance state (Holling, 1973). Systems are seen as having a single equilibrium, and maintaining stability near that state is the primary objective (Salter and Tarko, 2019).

From an instrumental position, technology is a neutral or universal object for humans to use to achieve progress (Feenberg, 2008), i.e., it is "the embodiment of scientific principles and rational knowledge" that can be used for different purposes, regardless of social-cultural context (Ahlborg et al., 2019). Instrumental approaches typically invoke technological determinism, positing that "the uses made of technology are largely determined by the structure of the technology itself, that is, that its functions follow from its form" (Kline, 2001; Postman, 1993). They also rely on "technological imperatives," often expressed in needs-based terms due to technological functional requirements determined, in this case, by corresponding changes in the practical needs of society, thus implying different structures and practices in keeping with technological determinist models.

However, more technological interactionist models point to the intrinsic ways in which technology shapes and is shaped by societal interactions, emphasizing the socio-contextual systems in which it is embedded and derives meaning and use. It involves the (reciprocal) interaction between technological and social change, showing how behavior is affected and sculpted through interactions. Moreover, human interactions are critical determinant features of these systems. The nature of socialization in an urban setting is obviously central to recipients and as determinants of resilience effects, and human interactions in this sense are defined within and across various levels and units of analysis, including the individual. Therefore, these interactions are constituents of system capabilities as contextually determined, such that urban resilience is associated with the capacity of individuals, communities, organizations, and systems within a city to survive, adapt, and prosper despite various stressors or disturbances (Irani & Rahnamayiezekavat,2021; Spaans & Waterhout, 2017). Resilience in this sense has been extended to socio-ecological systems that "involve both natural/ecological and human/social components that interact to affect system dynamics" (Koontz et al., 2015), such as cities. This approach to resilience explicitly captures social and ecological elements and dynamics (Adger, 2000; Folke, 2006).

Intrinsic perspectives also indicate that technology can transform the resilience of a system (cf. Anderies et al., 2004), but additionally allow for the possibility that the effects can be either positive or negative depending on the particular circumstances at play. For example, some socio-ecological approaches directly account for the dynamics of technology — i.e., technology as an inherent feature of a system (Smith & Stirling, 2010). This point is captured in the concept of socio-technological resilience, specifying how technology is intertwined with people, organizations, and institutions (Amir & Kant, 2018). These systemic approaches offer a more encompassing view of resilience, suggesting how social-technological-ecological interactions can mitigate and/or perpetuate complex problems (McPhearson et al., 2021). As such, "society, technology, and the environment" are "co-constituted and co-emergent entities" (Ahlborg et al., 2019), with resilience understood as an endogenous systems component.

2.2. Governance and resilience

Cities are multifaceted systems in which governance provides an essential basis for resilience, the achievement of which rests on the active role of technology in urban management and planning processes (Irani & Rahnamayiezekavat,2021). However, one of the main challenges for governance in relation to resilience, of course, is the connection between technology and its social effects. Governance is needed to mitigate and avoid the negative implications of technology for resilience (Ahlborg et al., 2019). As an integral component of governance, institutions — reflecting the "rules of the game" — are particularly important in this regard (Koontz et al., 2015). In fact, "the city forms a complex ecosystem of places, people, and machinery, bound by institutions" (Feinberg et al., 2021).[3] Institutions are then the key link among social, ecological, and technological systems, thus intimately and intricately intertwined (Folke et al., 1998; Anderies et al., 2016). System responses and capacities for adaptive action depend crucially on institutions (Adger, 2000), underscoring the importance of stable economic and social institutions as bases for resilience and sustainable development (Herrfahrdt-Pähle & Pahl-Wostl, 2012). "Social rules are the basic constitutive unit of institutional arrangements and, as such, they represent the conceptual backbone of resilience analysis and design" (Aligica and Tarko, 2014). Accordingly, one cannot consider resilience without considering institutional factors; they are the key to analyzing resilience.

Moreover, the ability of institutions "to cope with and bounce back from crisis or disaster without system collapse" and appropriately adapt and innovate over time to ensure resilience over the longer term is a critical concern (Lockhart, 2020). With this in mind, "institutional resilience" is about managing continuity and change in a way that will not damage the system and lead to waning trust in the institutional setup (Folke et al., 1998). Institutional resilience is the capacity "of a social system (society, community, organization) to react and adapt to abrupt challenges (internal or external) and/or to avoid gradually drifting along destructive slippery slopes" (Aligica and Tarko 2014). Governance strategies for promoting resilience must consider technology choice, use, and control (Smith and Sterling, 2010); they are essential for institutional legitimacy and trust, which are vital determinants of resilience in both pragmatic and moral terms as translated in instrumental and intrinsic approaches (Suchman, 1995).

2.3. Analytical matters

Resilience is intrinsic to the smart city concept, with technology being a primary instrumental means to promote it (Kummitha, 2018). AI techniques, including machine learning, natural language processing, computer vision, and robotics, combined with various sensing mechanisms and big data, constitute the emerging technological foundations of the smart urban landscape, promoting smart operations and planning to transform the city into a large and complex system that "senses, thinks, and acts" (Chiya and Panfil, 2020). Such technologies promise to make cities more resilient and sustainable — to add value and vigor to the socio-ecological binomial (Santos et al., 2021), particularly by intelligently supporting and augmenting activities tied to urban planning and preparedness, as well as response and recovery efforts. AI is ultimately seen as an instrument for achieving "social good and other desired outcomes and futures for all humans and non-humans" (Yigitcanlar et al., 2020). However, such aspirations may be exaggerated, especially in light of the intrinsic social and ethical issues tied to the use of AI, which can militate against societal objectives if appropriate institutional levers and processes are not in place.

Of course, AI is certainly not new. Conceptualizations of "thinking" machines go back centuries (Mayor, 2018). Further, there have been multiple waves of AI innovations beginning with the birth of symbolic AI in the 1950s (Russell & Norvig, 2021). However, AI systems have become smarter over time — and, arguably, in this sense, more human-like. Current capabilities of AI include perception (e.g., audio, visual, textual, and tactile), decision making (e.g., resource allocation), prediction (e.g., disease incidence and weather forecasting), automatic knowledge extraction and pattern recognition (e.g., facial recognition), interactive communication (e.g., social robots or chatbots), and logical reasoning (e.g., theory development from premises) (Vineusa et al., 2020). Yet, humans remain superior to (are smarter than) machines in several areas, including social and emotional intelligence, use and retention of tacit knowledge, creativity, and inductive reasoning. Thus, AI capabilities may be narrow relative to some human capacities — but they are advancing quickly. Indeed, we are inching closer and closer to a scenario in which machines would be on par with humans in every possible way.

AI works hand-in-hand with big data, which generally pertains to fast-moving, voluminous data — both structured and unstructured varieties — that cannot be handled using conventional tools and methods (McNeely & Schintler, 2021a). A plethora of interconnected systems of human and machine sensors, e.g., aerial vehicles, the Internet of Things (IoT), crowdsourcing and social media platforms, and mobile devices, are continuously and relentlessly churning out reams of data in and about urban environments. AI systems rely on big data to build and validate algorithms, referring to sets of rules that are ultimately used and extrapolated by AI to produce outcomes and recommendations (Schintler and Lee, 2021). AI also is a source of big data, namely in terms of machine-generated bits and bytes of information that has been processed or transformed using algorithmic tools and methods (Schintler and Fischer, 2018).

From an instrumental perspective, the principal benefit of AI applications is that they promote efficiency. AI is generally capable of creating, processing, and analyzing information much faster — and in some cases, more effectively and productively — than humans and organizations, as well as conventional methods and techniques alone. It does this through two related mechanisms: optimization and

[3] Emphasis added.

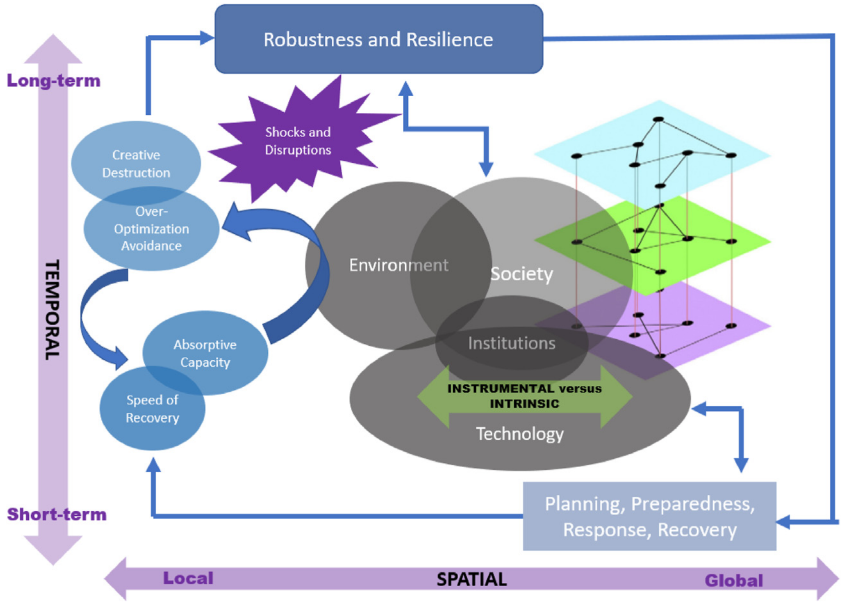

Fig. 1. Institutional, technological, and environmental societal systems in relation to dimensions and dynamics of robustness and resilience Source: Authors (original).

automation. First, AI is by design an optimization problem that uses algorithms to detect and classify patterns and make predictions and prescriptive suggestions subject to the maximization of some operational performance criteria. Second, new developments in AI are expanding the range of tasks that can be automated using the technology. More specifically, automation capabilities are no longer limited to activities that involve routine manual and routine cognitive skills (e.g., moving objects or processing and organizing information) but now also those that rely on non-routine skills (e.g., interacting with customers or patients). Accordingly, AI systems operate to enhance urban resilience by optimizing and automating disaster and crisis planning, preparedness, response, and recovery functions and endeavors. Furthermore, AI is creating "novel connections between humans, machines, and the living planet" that further amplify such capabilities through network effects and dynamics (Galaz et al., 2021). In this regard, AI is increasingly integrated with more traditional networked digital platforms and devices (e.g., the Internet and mobile telephones) to invoke notions of smart and connected cities and to create new and innovative "social machines" with human-machine (and machine-machine) interactions, collaborations, and systems that are capable of sensing, reasoning, judging, and learning in efficient and evermore intelligent ways (Schintler and McNeely, 2019).

On the other hand, the use of AI comes with various social, legal, and ethical challenges, downsides, and dangers that can detract and diminish efforts to maintain, build, and enhance urban resilience (Shackelford & Dockery, 2020). Algorithmic decision making is "prone to errors, biases, and false logic or mistaken assumptions," also raising issues in relation to privacy, transparency, and accountability, particularly since the rules embedded in AI are often known only to the developers or owners of related systems (Anderson et al., 2018). Such problems can undermine key determinants of community resilience, including "community capacity, social and human capital, knowledge inclusion, participation, social innovation, and social equity" (Arafah & Winarso, 2017). Additionally, questions of values and other intrinsic aspects of AI technology are inextricably linked to problems like algorithmic bias, invasions of privacy, and safety hazards, as well as the formal and informal rules for ameliorating or fixing these problems in the first place. Finally, while emergent forms of social organization involving both humans and machines as active participants are making cities more intelligent, they at the same time pose different and complex risks and vulnerabilities that can potentially threaten and compromise urban resilience (Galaz et al., 2021).

Such issues lead us to a broad consideration of the relationship of technology to individuals, organizations, and society and how they affect each other. Accordingly, we operationalize the concept of urban resilience in reference to AI by identifying characteristics associated with institutional dynamics. Emphasis is placed on various aspects of resilience as they relate to one another to allow us to unpack the complex institutional relations and layers of AI interactions that are central to understanding resilience and the city. In addition, while institutions conventionally have been understood as constraints and rules that humans devise to shape social interaction (North, 1996), machines now often are considered to have the ability to fulfill that role (Bridges, 2016). In fact, in the sense that it embodies a set of rules codified as algorithms, AI itself can be understood as an institution (Napoli, 2014), performing regulatory functions, constraining and facilitating behaviors, actions, and preferences of individuals and organizations (Katzenbach, 2011). As such, AI is sometimes referred to as a "code of law" (Lessig, 2006).

It is in this vein that questions of governance arise. As discussed, institutions are sets of rules that give meaning to and regulate social activity in a patterned way, and institutionalization is a process by which those rules become legitimated and trusted (and taken for granted). Institutionalized rules define related patterns of "appropriate" activities and strategies and constitute their purposes and legitimacy, ultimately facilitating trust, which is crucial for resilience (Suchman, 1995). Through this lens, the city is seen as an increasingly integrated socio-spatio-technological system around institutionalized rules that affect the units within them, and cities tend to select and engage legitimated strategies from the wider institutional context. The forms of activities and mechanisms by which decisions are made and resources distributed and mobilized in cities are shaped, at least in part, relative to those prescribed in the institutional context and broader system, and to forms of interactions and socialization that are being engendered by AI. They also may be challenging and replacing existing social and institutional mechanisms over time (Koutroumpis & Lafond, 2018). Therefore, the perspective employed here invokes AI and resilience not merely in terms of instrumental goal-oriented activities. Rather, the depiction of AI and resilience in terms of adaptive capacities and practices is grounded in the view that their roles and activities are subject to institutionally defined rules and governance procedures. In this same sense, the city itself is a systemic and institutional actor.

Our analysis is organized around four principal dimensions that capture the essential dynamics, strategies, and relationships that define resilience: *absorptive capacity, speed of recovery, over-optimization avoidance, and creative destruction* (Ostrom, 2009). The first two dimensions are key aspects of robustness, whereas the latter two capture longer-term adaptability and resilience in cities. Taken together, these features offer an integrated strategy for addressing resilience as a critical characteristic of smart cities. We engage them as analytical tropes for examining how institutional relations and dynamics impact technological interactions relative to contextually specified approaches to resilience. The analytical problem here lies in the separation between ideas about technological instrumentalism and those based on intrinsic institutional constructions involved in relevant interactions. The idea of urban resilience in this sense is based on an image of the city as a systemic societal entity in which the institutional and technological environment shapes and is shaped by individual and organizational structures, relationships, and actions, and, ultimately, robustness and resilience, as depicted in Fig. 1. Again, emphasis here is on the instrumental and intrinsic nature of AI systems and how they work in tandem with and as institutions themselves to shape and affect the robustness and resilience of a city.

3. Absorptive capacity

The capability of a city to withstand shocks without a significant loss of functionality — i.e., to maintain stability and continuity in the presence of uncertainty and turbulence and to effectively recover from a disruptive event — requires planning and preparedness. To this end, cities must develop rules and protocols for coping with crises and disasters should they occur and to mitigate related threats in the first place. However, this is a daunting task. Not only is the degree of turmoil in the world increasing, disruptions also are becoming more complex, involving multiple interrelated economic, social, spatial, and technological systems within and across cities in intricate and dynamic ways that contribute to and compound uncertainty and risk (Reggiani et al., 2021).

In light of these circumstances, it is increasingly recognized that urban resilience planning and preparedness must adopt an encompassing, systemic, participatory, and long-term orientation and vision to effectively craft strategies for avoiding and attenuating shocks in cities and systems of cities (Eraydin, 2013). While a range of technical and multidisciplinary tactics can be applied to analyzing urban subsystems, identifying critical vulnerabilities, and assessing policy and operational interventions to address the demands of resilience planning, instrumental and intrinsic concerns across the board can be viewed relative to elements of rational and communicative anticipatory strategies.

Capacities for rational planning are not only encumbered by increasing uncertainty, change, unrest, and complexity, they also are constrained by information overload. Indeed, the volume of information and data is expanding exponentially and much more quickly than the ability to acquire, store, process, and analyze it (Schintler & McNeely, 2021). In this context, the share of inaccurate and irrelevant data compared to useable and trustworthy data is growing, contributing to significant amounts of "data smog" (Shenk, 1997). This problem is exacerbated in magnitudes of order during a crisis or disaster, as witnessed in recent pandemics, thus adding noise and imperfections to historical archives of events, making it more difficult for cities to learn from and develop valid and appropriate models based on prior experiences. In general, the ability of conventional planning methods and human and organizational input to grapple with such challenges is often insufficient. Because of this, rational planning might be viewed as "super-human" and, consequently, cities often are forced to "satisfice" or "muddle through" problems in an incremental fashion (Lindblom, 1959), which is suboptimal for resilience planning (Eraydin, 2013).

Algorithmic solutions can help address such problems and reinvigorate planning as a rational process. As a matter of fact, AI systems are, by design, rational agents, purposively programmed to systematically and efficiently sense, analyze, and depict the world and to act and solve problems according to a specified set of goals (Parkes & Wellman, 2015). For example, AI algorithms can comb through troves of structured and unstructured historical data (e.g., regarding natural disasters) to discern and classify patterns and relationships, and connect massive amounts of data points to assess risk and vulnerabilities in ways not possible with traditional methods (Qadir et al., 2021). Moreover, predictive AI analytics are ideally suited for anticipating complex events and their effects on urban communities (e.g., pandemics or extreme weather) (Syifa et al., 2019; McNeely, 2021), addressing analytical challenges posed by the multiplicity and variability of parameters involved in modeling such occurrences (Yu et al., 2018). Also, AI can be used as a tool for assessing the efficacy of rules and strategies for coping with shocks (Qadir et al., 2016), including in an automated fashion (Munawar et al., 2022). Although more conventional approaches (e.g., dynamic systems modeling) bear similar benefits, the instrumental point here is that AI systems can more swiftly and systematically process and analyze data and identify and solve problems related to difficulties of rational resilience planning.

Another advantage that typically is posited regarding AI over traditional analytical and computational tools is that it minimizes uncertainty through optimization mechanisms similar to those in the human brain. For instance, deep neural learning — a complex machine learning model that comprises multiple interconnected and parameterized layers — is programmed to minimize noise and uncertainty in the learning process (Walchover, 2017). At the same time, however, AI can contribute to and magnify ambiguity in various ways (Wu & Shang, 2020), which can cloud, complicate, and corrupt the potential for rational planning. In particular, uncertainty arises in situations where the data used for developing an AI system are imperfect or incomplete, or the nuances of the problem being analyzed (including social rules and values) are not adequately understood or captured in the model in the first place. This is the essence of algorithmic bias. In fact, allowing machines “to take charge of unclear or even harmful processes and structures” is dangerous because they “may calculate an optimal solution for the wrong problem or target" (Wu & Shang, 2020).

The outcomes of modeling and analysis of urban risks and vulnerabilities (and instrumental rationality) are subsequently used as constraints to the decision-making activities, where communicative planning is a necessary and salient feature of the process (Eraydin, 2013). The communicative ideal is characterized as an "inclusive critical discussion, free of social and economic pressures, in which interlocutors treat each other as equals in a cooperative attempt to reach an understanding on matters of common concern" (Habermas, 1984). Discrepancies between diverse needs and preferences, particularly in situations where value conflicts and moral challenges are present, are another source of uncertainty with the use of AI, raising a host of ethical concerns and challenges (Wu & Shang, 2020). However, AI detracts from capacities for dealing with such issues, especially since its use contributes to information asymmetries and power imbalances that contradict the egalitarian principles of communicative rationality. One serious concern in this regard involves the opaqueness of AI systems, which is particularly problematic in the case of deep learning, where there are countless possibilities for architecture design, including the selection of algorithms, parameterization schemes, and data for training and testing (Schintler and Lee, 2021). Compounding matters, “Big Tech” companies are playing an increasing role in designing, implementing, and managing AI systems in cities (Galaz et al., 2021). Commercial AI systems often are strategically developed as "black boxes," particularly for proprietary reasons and to preserve data confidentiality. Also, as mentioned, with rapid developments in AI, such systems are gaining more agency, autonomy, and authority in an intrinsic sense, putting humans at a disadvantage or replacing them, such that decision making on important matters is handed over to "code-driven tools" (Anderson et al., 2018). Accordingly, rather than human planners operating as knowledge mediators and brokers to help frame problems and develop solutions with public input, machines are increasingly playing this role.

A related matter pertains to digital divides. Some cities, and individuals and communities within cities, have relatively low (or no) access to AI technology and, moreover, lack the skills and knowledge to engage such technologies in productive ways (Galaz et al., 2021). In fact, vast swaths of the population do not have access, broadly defined, to related technology nor capacities for its safe and ethical use, thus disenfranchising and creating more societal asymmetries in privilege, voice, and power (Anderson et al., 2018; McNeely & Schintler, 2021b). Indeed, digital divides have been widening over time. As the capabilities of AI technology accelerate and expand, some cities and regions are falling further behind while others are progressing, to the extent that some analysts have framed the problem as a futile situation (Schintler & McNeely, 2019).

4. Speed of recovery

Even when faced with similar types and levels of turbulence, some urban areas recover more quickly than others (Lockhart, 2020). To respond effectively to related events, a city must have the right information at the right time and the right location. However, many incidents are highly fluid, where conditions change abruptly and unexpectedly, and related dynamics and effects can vary from one area to another, creating challenges for urban disaster and crisis response and restoration efforts.

Data-driven algorithmic approaches can help address such problems and, thus, are instrumental in enabling cities to return rapidly to equilibrium (Sharifi et al., 2021). AI analytics combined with geo-temporal big data provide the means for real-time surveillance, advancing capacities for location- and time-specific situational awareness. In this respect, standard planning methods and data sources (e.g., official government records) may fall short, especially since they tend to summarize and analyze information at fixed and extended durations (e.g., years or months) and in spatial aggregates (e.g., administrative boundaries). Geo-temporal big data, on the other hand, tend to have high velocity, streaming in on a continuous basis and with a precise geographic resolution, in some cases down to specific latitude and longitude coordinates. Such data, coupled with AI classification, pattern recognition, and predictive analytics, support the development of early warning systems, which are vital for sensing and anticipating vulnerabilities and risks before and during disruptions (Arslan et al., 2017). Moreover, geo-temporal big data and related AI analytics used for non-emergency purposes, can be applied during a crisis or disaster to address emergent informational and computational needs and demands. For example, COVID-19 led to the use of wastewater analytics for tracking the novel coronavirus in urban communities, overcoming the limitations of epidemiological instruments and indicators not tailored to the nuances of the pandemic (Larsen & Wigginton, 2020).

Real-time AI predictive analytics coupled with big data enable "on-the-fly" assessments and understandings of how conditions during a disruption change vis-à-vis rules in place and how related strategies should be adapted on the spur of the moment. In this respect, "nowcasting,” which uses AI to make predictions of the present, very near future, and very recent past, is especially beneficial. For instance, such tools have been used in recent pandemics for the ongoing evaluation and adjustment of non-pharmaceutical interventions, such as shutdowns, travel bans, quarantines, and social distancing (Oliver et al., 2020). Finally, AI-based prescriptive analytics can perform quick optimization to support agile decision making, e.g., to expeditiously pinpoint neighborhoods that most need immediate assistance or to identify the best routes to reach those locations in the aftermath of a natural disaster (Munawar et al., 2022).

Yet, AI also can jeopardize a city's efforts to recover swiftly from a disruption or catastrophe. Algorithmic bias, which produces distorted and imprecise outcomes — and, thus, is a source of misinformation — can have detrimental impacts by obfuscating and slowing down decision-making processes. However, even if the model is constructed properly, its application can still lead to interpretation bias,” in which an "AI-system might be working as intended by its designer, but the user does not fully understand its utility, or tries to infer different meanings that the model might not support," e.g., through misalignment of values (Galaz et al., 2021). Moreover, as mentioned, AI tends to contribute to outcomes and decisions that misrepresent and disfavor women, minorities, and other disadvantaged individuals and communities (Anderson et al., 2018). Accordingly, biases embedded in and engendered by AI analytics for urban response and recovery can lead to ineffective (and unfair) solutions, e.g., where particular areas do not receive proper attention in time or at all.

Additionally, AI itself is vulnerable to disruptions (e.g., security breaches) that can corrupt decision making during and following a disturbance (Galaz et al., 2021). This situation has become increasingly problematic given that related systems are deeply entrenched in complex networks within and across cities. In addition to dismantling access to such tools during a crisis, nefarious agents can hack and reprogram the rules embedded in AI systems to advance their own political, economic, or other interests and motivations. As such, AI systems themselves, in their instrumental guise, can be weapons. Note that here we are not referencing "killer robots," per se. (We will leave that to the realm of science fiction for the time being.) Rather "AI is creating a world where reality can be manipulated in ways we do not appreciate," mainly through the use of AI-generated media such as "deepfakes" (a fusion of "deep learning" and "fake") as well as material objects (Anderson et al., 2018). For example, during the coronavirus pandemic, hackers have tampered with facial recognition systems, using a myriad of AI techniques to alter images and videos and even to create special masks to serve their own intents and purposes (Atrakchi & et al, 2021). Cyber-security policies and strategies aim to mitigate cyber vulnerabilities, but, frankly, related efforts have been somewhat ineffective. Specifically, it is a "spy-versus-spy" problem in which the "good guys" and the "bad guys" are in a perpetual loop to outwit each other.

During a disruption, two-way communication between urban management officials and the public is of the essence. Lack of operative communication can lead to "inadequate, ineffective, or delayed actions" (Sharifi et al., 2021). In this regard, cities have come to rely heavily on social media platforms. However, in addition to and over and beyond internal digital divides which preclude some parts of the population from accessing, using, and benefitting from such fora, online social networks have become infiltrated with "social bots," i.e., AI-enabled software agents — and their presence in digital media is far from trivial.[4] While bots can play a beneficial role by distributing automated messages to the public, they also are notorious for spreading misinformation and disinformation, thereby negatively impacting communication efforts. Moreover, the growing presence of AI agents (machines) in networks of various types is catalyzing new social and organizational dynamics marked by turbulence and instability, where systems are perpetually pushed in and out of equilibrium. The use of algorithmic trading in financial markets and its effects on chaotic dynamics in such systems (e.g., "flash crashes") is a classic example. In this way, then, bots can detract from urban resilience and robustness by compromising a city's ability to maintain continuity, which also can slow down speed of recovery.

5. Over-optimization avoidance

The problem of over-optimization also can compromise urban resilience. In general, an organization or system exclusively designed for maximizing efficiency may be susceptible to vulnerabilities and unexpected ambiguities.[5] More specifically, "the performance and robustness of optimized designs with respect to the uncertainty" they were designed to address are "accompanied by extreme sensitivity to additional uncertainty that is not included in the design" (Carlson & Doyle, 2002: 1424). In fact, the optimization process itself can contribute to "black swans," unforeseen events with potentially severe consequences (Carlson & Doyle, 2002). A central problem is that, "as systems become increasingly optimized and efficient, they also become more brittle and vulnerable to undesirable" regime changes, creating "abrupt, unwanted, and sometimes irreversible changes" (Galaz et al., 2021). Accordingly, AI systems designed to maximize robustness (i.e., short-term resilience) can compromise resilience over a longer-term horizon (Yardi, 2020), a problem which is particularly problematic if efficiency is prioritized over redundancy and diversity, two factors critical to the long-term survival of a system like a city (Galaz et al., 2021).

As a practical matter, one of the dangers in this regard is that urban managers and planners may use "off-the-shelf" software developed for other purposes (e.g., business intelligence), which is a potentially troublesome practice since intrinsic values and related interests, framings, and motivations in different contexts may not be aligned. For example, private sector interests may be more in keeping with efficiency in terms of optimizing profits and rates of return on investment (especially in the short-term), rather than social values (Schintler, 2021) and societal sustainability (Arogysaswamy, 2020). Accordingly, commercial AI systems may be not only over-optimized for the present but also mis-optimized by being grounded in principles that are incongruent with efforts to promote urban resilience. Again, this underscores the importance of contextual specification and treating resilience as a sustained and long-lasting process, and for ensuring that the appropriate values are reflected and advanced in resilience planning, analytically and otherwise (Eraydin, 2013).

AI optimization based on past challenges and experiences also can inadvertently create previously nonexistent vulnerabilities as well as unanticipated uncertainty (Aligica and Tarko, 2014; Salter & Tarko, 2019), placing additional stress and strain on a city. Generally speaking, optimization and related decision making based on historical data make for a risky affair, especially without appropriate technical solutions and ample consideration of the particular circumstances at hand. Indeed, the real world is constantly in flux, and crises may occur at any moment. In fact, "during turbulent times in particular, predictions based on historical data are easily distorted" (Wu & Shang, 2020). Thus, an AI system that blindly optimizes efficiency based on prior crises and disasters can work to the detriment of a city's resilience.

[4] https://www.npr.org/sections/coronavirus-live-updates/2020/05/20/859814085/researchers-nearly-half-of-accounts-tweeting-about-coronavirus-are-likely-bots.

[5] This situation is the idea behind Highly-Optimized-Tolerance (HOT), a mathematical theory initially developed by Carlson and Doyle (2002) and later applied in relation to ecological resilience (Anderies and Janssen, 2013).

Somewhat paradoxically, a focus on maximizing efficiency also contributes to under-optimization — or in machine learning parlance, “underfitting” — which also can diminish urban resilience. That is, in doing so, an AI system may fail to properly consider and incorporate the distinct factors and dynamics inherent to a given city or region. An understanding and consideration of local norms, values, practices, and other contextual artifacts is necessary for fostering urban resilience (Anderson & de Tollenaere, 2020). On the other hand, tailoring an AI system to the specific social, institutional, and environmental characteristics of an urban area can contribute to the problem of "overfitting." Thus, the model may perform well for the community for which it was developed but, if transferred and applied to another place without being re-contextualized, can be ineffective and even dangerous (Galaz et al., 2021), an issue generally referred to as “transfer context bias” (Ahlborg et al., 2019). Of course, AI systems are not "generalists"; that is, they do not embody general-purpose intelligence that can be effectively applied from one location, situation, or time to another without compromising performance. Instead, they are specialists relevant to particular domains, depending on the data and information they have learned. This is the distinction between Artificial General Intelligence and Artificial Narrow Intelligence, respectively.

The distributional effects of over-optimization are compounded by the fact that cities are linked together locally and globally through vast and intricate economic, infrastructural, and social networks — both physical and virtual (Sassen, 2013). As already noted, AI is increasingly woven into these webs, with smart cities in particular deeply dependent upon networked AI systems of one type or another (Anderson et al., 2018). Accordingly, if AI is optimized for one city, it can have negative ramifications for other cities and could, for example, lead to "cascading failures" (Aligica and Tarko, 2014). Complicating matters is that the networks in which AI is embedded tend to be vulnerable in the first place. In particular, many large-scale networks (e.g., critical infrastructure or online social networks) possess scale-free properties that have evolved organically via self-organizing dynamics or by human design (Schintler et al., 2005). While highly efficient, a scale-free topology is extremely susceptible to shocks and disruptions and to widespread and interdependent failures (Schintler et al., 2004). All of this again highlights the dangers of over-optimization and emphasizes the need for a systemic and dynamic approach to urban resilience planning (Eraydin, 2013).

6. Creative destruction

Longer-term resilience, which is marked by adaptive capacity, self-organization, and transformation, is a function of "creative destruction" (Aligica and Tarko, 2014), i.e., a "perpetual process in which old modes of production and methods are discarded" and "more efficient methods take their place" (Lockhart, 2020).[6] Accordingly, innovation is required to transform rules in ways that ensure "better planning and preparation for future events" and shifts to better equilibria (Sharifi et al., 2021). Indeed, a disruptive event can be a catalyst for productive and innovative change geared toward enhancing resilience, as seen with the coronavirus pandemic which has accelerated the trend toward smart cities and automation and digitalization more broadly for that purpose. However, in order for a city or region to innovate in the first place, it must have the capacity to learn, particularly to cope with and adapt to new conditions and dynamics (Folke et al., 2002). In this regard, institutionalized learning and the ability to nurture a productive culture for systemic innovation are crucial (Cooke et al., 1997). Regions evolve and adapt based on learning processes that are fed with information and knowledge, among other things (Camagni & Capello, 2017), with AI being particularly apropos in this respect, as it is a source of intelligence and also is wired to learn (as in machine learning). However, from a more intrinsic perspective, this point also leads to fundamental questions: What is AI learning? Is it learning the “right” things? What should it learn with respect to facilitating resilience? As previously discussed, training an AI system to maximize efficiency or in reference to particular situations and contexts is, on the one hand, necessary. At the same time, this approach is fraught with technological and societal challenges, complications, and even dangers.

It is in this regard that questions of social justice and diversity are of particular note. Social justice and diversity are key elements linked to societal adaptations and assessments of innovation and resilience as embedded social processes. As such, they are especially pertinent to social, economic, and political agenda relative to institutional dynamics in today’s increasingly AI-driven world (Vineusa et al., 2020). However, even in the face of efforts to design AI systems with social justice objectives in mind, current trajectories reflect scenarios in which historic and structural inequalities continue to perpetuate, especially in the absence of rules ensuring that AI yields equitable outcomes and decisions (Anderson et al., 2018). In fact, digital technologies have already deepened inequality among and within cities for decades (Sassen, 2013). However, strategies aimed at protecting individuals, groups, or communities from problems associated with AI — which can occur through various means, e.g., job automation, privacy violations, and algorithmic bias and discrimination — have been argued as stifling innovation.[7] Of course, related issues arise in regard to what kind of innovations are valued relative to societal effects and consequences. Frankly, AI can contribute to inequality in various ways and can be interpreted as suppressing innovation accordingly. For example, assumptions about homogeneity are often made in AI, particularly in relation to individual preferences and intentions and to attributes of a community (Wu & Shang, 2020), such that it has the potential to contribute to mean reversion, i.e., a convergence of "averages" over time, which can further inhibit innovation.

7. Concluding remarks

In many ways, resilience is a cornerstone of existence in today's world — and for the future — and must be understood in a broader institutional context shaped by social, political, and economic forces. From this perspective, resilience is most appropriately

[6] Initially introduced by Schumpeter.

[7] https://theconversation.com/ai-developers-often-ignore-safety-in-the-pursuit-of-a-breakthrough-so-how-do-we-regulate-them-without-blocking-progress-155825.

conceptualized as the product of various interactive factors and processes, as summarized in Table 1 and highlighted in relation to the use of AI for urban management and planning. While from an operational perspective AI has prospects to promote resilience, the social and ethical issues and risks that come part and parcel with its use, along with profound changes occurring in cities as systemic actors, are increasingly woven into its social and organizational fabric, pointing to a number of instrumental and intrinsic provocations regarding AI and urban resilience.

As noted, appropriate governance and institutional levers — standards, policies, systems, processes, structures, and rules — must be devised and implemented to ensure that the legitimate and trustworthy use of AI for urban management and planning. To help inform the formulation, implementation, and assessment of relevant rules, protocols, and mechanisms, as well as the ongoing use of AI for managing disruptions in urban areas, a significant priority is the construction of reliable and suitable metrics and evaluation benchmarks. In this regard, policy analysis and related assessments must move beyond sole consideration of the individual risks and benefits of AI also to address higher-order impacts on communities, cities, and systems of cities in relation to resilience and sustainability. Furthermore, governance and oversight efforts must be woven throughout the entire AI lifecycle, from the inception of systems and applications to their final deployment and use (Dankwa-Mullan et al., 2021), since actions taken at each stage can ultimately have a bearing on resilience — for better or worse. Finally, while there is a need for top-down approaches to governance (e.g., regulatory and legal frameworks), bottom-up processes also should be considered, as rules that are established by users in a system like a city "are better known, understood, and perceived as being legitimate" (Anderies et al., 2004). Thus, they may be more effective, especially since they are contextualized relative to the particular resilience dynamics, conditions, and needs of a community and local context (Moraci et al., 2018).

However, a host of challenges arise in relation to governance given the complexity of urban systems and of resilience itself. One issue concerns the involvement of multiple stakeholders, including government, industry, and users within cities and all over the world, each having different and often competing views and logics (Shackelford & Dockery, 2020). Complex tradeoffs also are apparent, a principal one being obvious tensions between efficiency and resilience. Moreover, varying temporal, spatial, and organizational scales within and across cities further complicate matters. For example, urban management strategies and governance are local. However, as highlighted, cities are interconnected relative to internal and external systems, including the rest of the world, even more so in this era of globalization, again pointing to the need for a relatively coordinated yet flexible governance framework. Another complicating factor in terms of governance, as mentioned, is private sector interests. For example, the increasing presence of the aforementioned Big Tech companies in smart cities are of particular note, especially since they largely set their own rules regarding the development and use of AI systems (Arogyaswamy, 2020). Additionally, a point that must be stressed is that institutional change — e.g., in terms of regulatory reform or cultural shifts — is generally slow relative to the speed at which technology develops and should be a principal consideration in long-term resilience planning which, again, poses its own set of challenges. As we emphasize, AI and urban resilience are systemic in nature, and strategies should be devised accordingly and considered relative to institutional structures and dynamics.

A polycentric approach to institutions offers an adaptive form of governance that can help address some of the issues and challenges raised here (Koontz et al., 2015). A polycentric system encompasses multiple decision-making units, each of which can devise and enforce rules within some specified domain of authority (Ostrom, 2009) and is viewed as attuned to the particular milieu of a

Table 1
Resilience dimensions, mechanisms, and impact.

Dimension	Mechanism	Impact
Absorptive Capacity	Information Overload Management	Promotes Rational Planning
	Algorithmic Bias	Increases Uncertainty/Hinders Rational Planning
	Unreliable Outcomes	
	Lack of Transparency	
	Lack of Transparency and Accountability	Hinders Communicative Planning
	Increasing Machine (Decreasing Human Agency, Autonomy, and Authority	
	Digital Divides	
Speed of Recovery	Optimization	Promotes Quick, Efficient and "Smart" Decision-Making
	Automation/Efficiency Maximization	
	"Nowcasting," Smart Sensing, Real-time Prescriptive Analytics	
	Algorithmic Bias and Discrimination	Contributes to Wrong or Unfair Outcomes and Decisions
	AI as a Weapon ("bots," "deepfakes")	
	Automation/Natural Language Processing/Robotics ("bots")	Hinders/Promotes Communication
Over-Optimization Avoidance	Efficiency Maximization (Efficiency Maximization)	Optimizes Short-Term Resilience -Robustness
	Efficiency Maximization ("HOT")	Impedes Long-Term Resilience
	Value Misalignment	
	Lack of Contextualization	
	Networked AI	Contributes to Vulnerabilities—e.g., "Cascading Failures"
Creative Destruction	Machine Learning	Promotes Learning, Adaptation and Innovation
	Algorithmic Bias	Reduces Diversity/Stifles Innovation
	Reversion to the Mean	
	Lack of Contextualization	
	Governance of AI	Increases Diversity/Promotes Innovation
	Governance of AI	Stifles Innovation

community and promoting a diversity of perspectives (Salter & Tarko, 2019). In a polycentric system, institutions are characterized as "dynamic, adaptive, and flexible," rather than as "static, rule-based, formal, and fixed organizations with clear boundaries" (International Institute for Sustainable Development IISD, 2006, p. 6). As such, a polycentric institutional structure optimally facilitates innovation and socio-cultural adaptions and, further, enhances absorption capacity and speed of recovery by minimizing channels of communication (Aligica and Tarko, 2014; Salter & Tarko, 2019).

Interestingly, at least by design, blockchain can be viewed as the essence of a polycentric institutional framework (Murtazashvili & Weiss, 2021). In fact, blockchain might be more aptly referenced as an institution than a technology (Davidson et al., 2016). Blockchain is essentially a decentralized, distributed, and immutable ledger that records transactions between parties directly without third-party involvement. Each transaction is vetted and authenticated by powerful AI algorithms running across all the blocks and users, where consensus across the nodes is required to establish a transaction's legitimacy. Blockchain has other benefits for a polycentric institutional framework, the most important one being that it reduces uncertainty and, consequently, facilitates trust, which is crucial for resilience. In fact, blockchain is touted as a technology for closing the "trust gap." Also, the network structure of blockchain is distributed, which means that it is almost immune from catastrophic failures unlike other topologies (e.g., scale-free), although intrusions and unauthorized alterations do occur on the blockchain (Alkhalifah et al., 2020). Considering all this, is blockchain the golden key to urban resilience, or is it just a mirage in this regard? This is an open question. In any case, it is important to emphasize that blockchain runs on algorithms and, therefore, all the ways in which AI compromises urban resilience may apply as well. The same point applies to other forms of AI-enabled governance approaches, such as Explainable AI (XAI), which is presented as a way to enlighten the public about the inner workings of AI algorithms, including how and why they are being used, and to facilitate transparency and accountability. However, XAI raises its own set of ethical issues and related challenges McDermid et al., 2021).

In addition to mitigating the ethical and social downsides of AI through the use of appropriate governance and institutional strategies, there is a need to forge collaborative arrangements between humans and machines in a cohesive and legitimate fashion to facilitate urban resilience. In this regard, we must take stock of their relative capabilities, particularly to foster intelligence amplification and to understand the complexities that attend human intelligence versus machine intelligence models. Ultimately, trust and legitimacy are the name of the game at the end of the day, especially in anticipation of bringing humans into proper focus in this picture and creating a situation where "humans and machines dance together" (WEF, 2019) — all of which pushes us ahead to the next wave of disruptive technological and institutional change.

Conflicts of interest

We have no conflict of interest.

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