DOI: 10.1111/risa.14102

ORIGINAL ARTICLE

Smart cities at risk: Systemic risk drivers in the blind spot of long-term governance

Sadeeb Simon Ottenburger[1] | **Ulrich Ufer**[2]

[1]Institute for Thermal Energy Technology and Safety (ITES), Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany

[2]Institute for Technology Assessment and Systems Analysis (ITAS), Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany

Correspondence
Sadeeb Simon Ottenburger, Institute for Thermal Energy Technology and Safety (ITES), Karlsruhe Institute of Technology (KIT), Hermann-von-Helmholtz Platz 1, 76344 Eggenstein-Leopoldshafen, Germany.
Email: ottenburger@kit.edu

Abstract

In this article, we analyze "digital massification" in smart cities, that is, an ever-growing number of market participants, consumers, and Internet of Things devices with simultaneous accommodation of users to increasing disturbances and inconveniences due to data congestion—as a driver for systemic risk. We argue that digital massification phenomena largely escape societal awareness due to their protracted evolution and are therefore still in the blind spot of long-term governance. Our analysis makes methodological use of historical and relational analogy, and we introduce and elaborate concepts and terms that allow us to discuss the evolutionary nature of massification, that is, the foreseeable increasing probability of the occurrence of trigger events. Using the analogy to the history of road traffic congestion, we deduce that digital massification will most likely lead to a future "risk transition" where tolerated disturbances and inconveniences of the present will turn into systemic impacts. This insight calls for heightened sensitivity in governance to massification phenomena to ensure the long-term resilience of smart cities.

KEYWORDS
critical services, data congestion, long-term governance, risk evolution, smart city, systemic risk drivers

1 | INTRODUCTION

The ability to recognize harmful or critical environmental conditions and impending dangers in order to adapt to, reduce, or even prevent them in a timely manner is necessary for the survival of living beings or organizations. The introduction of new technologies, coupled with a steady increase in users and the resulting ever-increasing strain on infrastructure, can contribute to damage of systemic proportions in the long term if the associated, also increasing, loss of comfort is socially accommodated. This long-term phenomenon of risk-driving development should be considered with great attention, especially when it concerns complex systems of interconnected infrastructures deemed critical, as is the case in smart cities (Haggag et al., 2020). In the context of smart cities and digitalization, we discuss this phenomenon by introducing and elaborating on the concept of "digital massification." We classify massification as a driver of systemic risk due to the increasing probability and magnitude of triggering events, such as congestions. We see digital massification currently in full development; nevertheless, it is still in the blind spot of long-term governance.

The topic of "systemic risk" itself has moved into scientific focus, expressing a growing understanding of how in a context of major infrastructural transformations, increasing interconnectedness, and complexity and under the impacts of climate change even small disturbances or interruptions may push systems close to tipping points or result in regime shifts and systemically adverse situations (Helbing, 2013). Attributes of *systemic risks* as well as triggering events have been widely discussed (see Renn et al., 2020). In this article, we concentrate on *systemic risk* drivers, that is, drivers of systemic risk, by focusing on the long-term evolution of data congestions as trigger events. However, early awareness of drivers of systemic risk becomes even more difficult when associated with long-term evolutionary processes of small and incremental changes that can easily be accommodated into everyday life as mere disturbances or loss of comfort,

Both authors have contributed equally to this research article.

thus escaping societal awareness and debates before or even while they make the transition to systemic impacts.

1.1 | Smart cities and systemic risk drivers

We argue, therefore, that a fundamental awareness of long-term evolutionary processes as potential systemic risk drivers is currently lacking with regard to potential data congestions within complex critical infrastructure systems in smart cities. We contend that blind spots in long-term governance perspectives are possible and even already exist. In abstract terms, the evolutionary long-term process we primarily consider in this article is the steady increase in market participants, consumers, and Internet of Things (IoT) devices. This process started decades ago and is likely to evolve over many decades into the future. As we will show by drawing an analogy between future smart city data traffic and the past development of road traffic congestion, the process of incrementally increasing data congestion runs the risk of creeping societal habituation, naturalization, and accommodation to initially congestion-induced drawbacks, inconveniences, or comfort losses. These may escape societal awareness until, or even when, they eventually amount to significant levels and make the transition to systemic impacts.

Exemplarily, a prerequisite of massification in smart grids—as a dominant sub-infrastructure of smart cities with densely interwoven and continuously digitized and converging infrastructures (Büscher et al., 2020)—is the current standard of an almost completely liberal market for urban digitalization (Parag & Sovacool, 2016). Neither the individual IoT device nor the individual company, sector, or user acts as a systemic risk driver for data traffic congestion phenomena, but the overall process of massification. Smart cities may therefore experience "risk transitions" at some point in the future, since massification is associated with citizens accommodating to ever-increasing data traffic congestions and thus with unawareness of a long process of risk evolution.

1.2 | Overview of the article

This article looks at long-term developments in relation to systemic risk and uses the method of historical analogy to draw attention to existing blind spots in the prevailing awareness of systemic risk drivers in the context of digital transformation. We present our finding that drivers of systemic risk are rarely addressed in the literature and that long-term evolutionary processes and societal accommodation phenomena as drivers of systemic risk in smart cities are currently neither debated nor discussed (see Section 2.4).

In Section 2, we outline the methodological approach of the article and present definitions of the key terms in our discussion. In Section 3, we analyze massification as a driver of long-term systemic risk evolution in smart cities by drawing a historical and relational analogy between vehicular massification in road traffic and digital massification in data traffic systems.

On this basis, we discuss in Section 4 that data congestion and increasing delays in digital services, although not currently recognized as a systemic risk driver but rather as an inconvenience, may have significant and direct adverse effects on the security of critical services in smart cities in the long term. With regard to data traffic congestion, we argue that smart cities are currently in an early phase of such continuous processes in the context of digital transformation and that societal accommodation is already taking place, which increases the likelihood of a future transition from inconveniences to risks.

We conclude in Section 5 that blind spots in awareness of long-term systemic risk drivers in society, governance, and urban resilience planning need to be recognized and that increased attention needs to be paid especially to slowly evolving drivers of systemic risk, such as digital massification.

2 | METHODOLOGICAL CONSIDERATIONS, TERMS, AND DEFINITIONS

The main purpose of this section is to provide an argumentative basis for analyzing drivers in the historical and longitudinal risk evolution process that initially manifest in non-critical contexts or dimensions but may evolve into major causes or triggers of relevant impacts and even systemic risks in complex systems prevailing in the future.

2.1 | Methodological considerations

When examining systemic risk drivers, we essentially look at the increase in the probability of triggering events, for example, congestions. The consideration of long-term risk evolution, as discussed and defined in this article, is particularly sensitive to limitations and uncertainties since there is no historical experience with data traffic evolution in smart cities on which to reliably base predictions and forecasts. Moreover, even with the statistical data available from the recent past, it often remains unclear how to distinguish causal and correlational relationships between elements (Barrowman, 2014) to the extent that, with increasing degrees of uncertainty, prospective risk assessment is at worst based merely on conjecture (Loveridge, 2009, p. 150). Studies in the field of financial risk assessment confirm that the "rationalist view that we live in a world of only calculable risk is too simple and leaves us with a dangerously incomplete view" (Nelson & Katzenstein, 2014, p. 363).

We therefore decided to use a relational and historical analogy between vehicular road traffic and digital data traffic as an appropriate heuristic to consider systemic risk drivers and risk evolution in smart cities. The method of relational and historical analogy, with due consideration for its possibili-

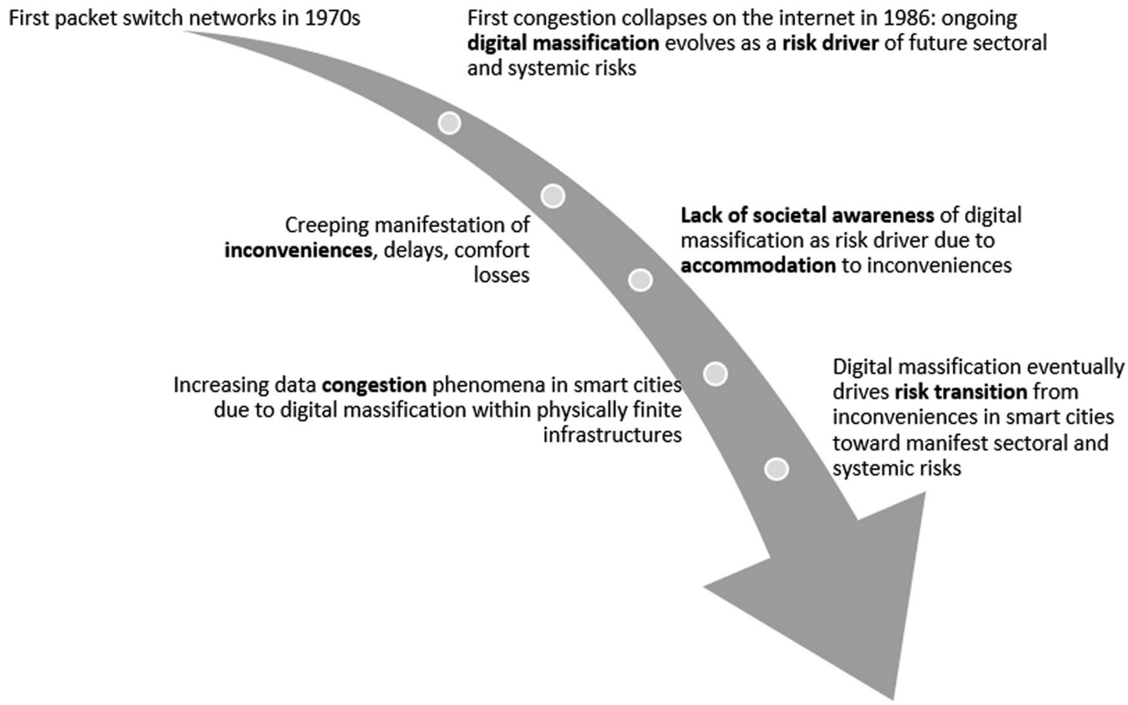

FIGURE 1 Continuous increase in systemic impact or risk evolution and risk transition driven by digital massification in the internet and information and communication systems more generally. *Source*: Authors' own compilation

ties and limitations (Ravn, 2011), helps deal precisely with future "conditions of uncertainty while operating with indirect evidence" (Flick, 1991, p. 64) and serves as a cognitive tool for making "heuristic transitions […] from known reality to previously unknown reality" (Syrovatka, 2000, p. 447).

2.2 | Massification and congestion

We begin by defining our abstract concept of massification[1], which we explicitly present and discuss in this article as a *driver* of systemic risk (and not as a systemic risk itself) that is still little discussed in science and policy. In the case of the information and communication infrastructure of smart cities, we see digital massification characterized by the following two key attributes in relation to a given physical and ultimately finite infrastructure:

1. Steady increase in market participants, consumers, and IoT devices using this infrastructure and associated deterioration effects that show in time losses, failures, and service quality degradation due to congestion.
2. Continuous accommodation of society to deterioration effects due to congestions and time losses.

As shown in Figure 1, this process of digital massification already started decades ago and is likely to evolve over several decades into the future. As we can already observe today, it is accompanied by creeping societal habituation, naturalization, and accommodation to initially inconveniences, delays, or comfort losses that have not yet resulted in significant systemic impact and damage and are not yet in the process we call risk transition.

As "smart" has become an important leitmotif in urban planning (Connolly et al., 2016), our concern about risk drivers and what we refer to as "risk transition" gains traction. This is especially true when more and more engineering solutions for critical infrastructures will be affected, for example, when a steady growth in market participants, consumers, and IoT devices leads to higher frequencies and growing extents of congestion in the information and communication sector. Here, we can expect potentially high impacts from data traffic congestions related to convergent critical services, but also tendencies toward societal accommodation.

2.3 | Massification as a systemic risk driver

Before turning to massification as a driver of systemic risks, we need to briefly address the concept of systemic risk itself. Systemic risks are referenced, for example, in the context of complex socioeconomic systems (Sterman, 2000). Here, a single trigger event, which may be the failure of an individual IoT device or a behavior change by some or many market participants or consumers, can result in a chain of stresses or failures, known as cascades, or in feedback loops,

[1] Close to our understanding of the term massification and its dynamics comes the "massification hypothesis" in educational research (Fox & Wince, 1975), which seeks to explain detrimental effects on the educational system due to mass enrollment.

or in unforeseen critical dynamics due to network interactions, which may lead to so-called tipping points and regime shifts with adverse consequences for society (Helbing, 2012). Triggering events are not necessarily associated with the failure of an infrastructure element (Helbing, 2013) but also with significant congestion and time loss related to information and resource flows.

Extreme events caused by climate change, the collapse of certain technical and organizational infrastructures, including financial systems, or an increase in vulnerability of supply systems and supply chains themselves are to be seen as major drivers of systemic risk. However, it is important to note that not only exogenous influences or the failure of individual system units can induce critical system states. Endogenous processes that lead to system-scale effects must also be considered serious causes of crisis situations. This is what Bak (1997) referred to as self-induced or self-organized criticality.

Since the above causes can be mutually dependent and socioeconomic systems are characterized by complexity and the interconnectedness of many subsystems, we are, in the case of smart cities, confronted with highly nonlinear dynamics in a system of systems endowed with large stochastic uncertainties. With the increasing digital networking and automation, a better understanding of systemic risk is needed not only in a global context but also at the regional and urban level (Weisbrod et al., 2003), not only in timeframes of weeks, months, or years but also in timeframes of minutes, hours, and days. This is all the more needed when various critical supply systems are involved and the security of supply to local populations is a focus of long-term governance.

Complexity is a widely recognized attribute of systemic risk, to which we add the evolutionary process of massification as a driver of congestion-related trigger events may themselves lead to systemic risks if they occur on the level of critical or lifeline infrastructures. As we shall expound in more detail below, the continuous and slow increase of particles in critical lifelines resulting from an intensification of data packets by a growing number of market participants, consumers and IoT devices makes delays and congestion more and more likely. Congestion and delays on critical lifelines not only mean a functional impairment of the affected lifeline itself, but also entail short- or medium-term negative effects on many downstream critical infrastructures, as is the case with car traffic. This may result in further failures and the possibility of damage on a systemic scale, which qualifies massification as a driver of systemic risks.

2.4 | Systemic risk drivers in the blind spot of societal awareness

After this condensed insight into the abstract nature of systemic risk, the question arises whether there are drivers of systemic risk that still elude general societal awareness. Our literature review revealed that most of the studies on systemic risk or on drivers of systemic risk relate to the financial sector or to the context of business continuity management, dealing, for example, with correlations between events and decision variables in terms of optimized investment or with risk drivers to reduce supply chain risks (Bierth et al., 2015; Haubrich et al., 2013; Hautsch et al., 2015; Liu et al., 2017; Tarashev et al., 2010; Weiß et al., 2014). Knowledge of risk drivers in the financial world has been enhanced not least due to the global financial crisis of 2007/2008, which was primarily caused by individual companies or institutions in the financial industry taking as much risk as their shareholders would allow, without considering the systemic implications. The financial crisis revealed the multiple dimensions of complexity and interrelation, the cascading dynamics within and across sectors and levels, and ultimately of systemic impacts. Since then, the continuous measurement and monitoring of systemic risk and associated risk drivers has been a major concern of financial regulation. Moreover, we found references to the term “risk driver” in the field of health as well, often used analogously to the more widespread term “risk factor” (Halden et al., 2021; Moheet & Seaquist, 2013; Tacconelli, 2009).

A key finding of our literature review is therefore that besides only limited disciplinary attention to systemic risk drivers, which so far excludes digital massification in smart cities, there is also ambiguity within the concept of systemic risk driver as such. In considering different time scales at the different levels of analysis, we found that analyses of systemic risk drivers have so far not adequately conceptualized the incremental, creeping, and continuous processes of deterioration. When accompanied by societal accommodation over several years or decades, these processes may have systemic effects that lead to a risk transition.

3 | HISTORICAL AND RELATIONAL ANALOGY: MASSIFICATION AND CONGESTION IN ROAD AND DATA TRAFFIC

In road traffic today, we can see the multiple indirect deterioration effects of high levels of congestion, which have assumed systemic proportions. We can trace the gradual development from an initially relatively smoothly functioning road traffic system to increasing inconveniences, drawbacks, and comfort losses due to traffic congestion to a stage of risk transition and a level of damage that is meanwhile recognized as systemic risk. Looking at digital massification and incremental societal accommodation to data congestion, our heuristically based historical and relational analogy suggests that smart cities are currently in an early phase of massification.

3.1 | Road traffic massification and vehicular congestion

Germany can be considered an ideal-type car friendly society, and its *autobahn* has a global reputation. From a systemic viewpoint, the dynamics of massification have repeatedly pushed the German highway system to its physical limits, leading to a continuous and dramatic expansion of road infrastructure and transport networks within and between cities (Kraftfahrt-Bundesamt, 2022; Statista, 2022b), accompanied by incremental societal accommodation to congestion: the first German highway between Cologne and Bonn, about 20 km long, was opened in 1932. In the 1960s, West Germany's booming economy accommodated nearly 4.5 million passenger cars on some 2500 km of highway. The first ever traffic jam in Germany was recorded in the summer months of 1963, and the total length of traffic jams reported that year was 33 km. In 2020, some 48.5 million passenger cars were registered in Germany, roughly a 10-fold increase over the 1960s. In addition, millions of German trucks as well as internationally registered vehicles use Germany's highways, the length of which has increased about fivefold compared to the 1960s to about 13,000 km today. Despite massive infrastructure investment and expansion, the physical bottleneck in the sociotechnical road traffic system in Germany is the provision of road space: on German highways in 2021, the length of traffic jams amounted to 850,000 km due to the rise in vehicles and drivers (Statista, 2022a), around 685,000 congestion events were counted (Statista, 2022c), and Germans spent close to 350,000 h in highway traffic jams (Statista, 2022d).

This historical case is instructive in two ways. First, it illustrates the process of initially incremental degradation, loss of comfort, or inconveniences due to the continuous increase in vehicle traffic in a limited physical environment. Second, the sociotechnical evolution of road systems in Germany and worldwide has been accompanied by unintended secondary effects in the form of creeping societal accommodation to emerging well-being losses from increasing congestion and associated time losses causing direct and systemic damage.

In the international context, this risk transition has been demonstrated in the dimensions of economy and health (Jayasooriya & Bandara, 2017; Weisbrod et al., 2003). The negative economic impact of road traffic congestion, considered a type of systemic risk, has been the focus of international research for many years. The monetary costs resulting from lost or increased travel time are related to additional productivity costs associated with available work time, logistics, just-in-time production processes, and so on. This is particularly evident in urban and regional contexts, where transportation measures may reduce travel time but increase overall traffic volumes. Other systemic impacts of traffic congestion include shrinking market segments and challenges to economies of scale in urban areas. According to models by Levy et al. (2010), the negative economic impacts of congestion in the United States, such as fuel waste and time loss, will continue to increase; the associated costs could amount to 100 billion US dollars in 2030.

Furthermore, some significant health risks from air and noise pollution (Moore et al., 2003) can be attributed to increased traffic density, risks that are particularly relevant for congested metropolitan regions (Zhang & Batterman, 2013). For the US context, Fields and Renne (2021, pp. 4–5) summarize that motorized traffic causes about 37,000 deaths, 2.7 million injuries from accidents, and 53,000 premature deaths from air pollution annually. On a global scale, the World Health Organization estimates 1.35 million deaths from vehicle crashes and 4.2 million premature deaths related to the transportation sector (Fields & Renne, 2021).

To speak of systemic risk here is justified because the economic and health impacts mentioned above can be classified as systemic damages, as a result of systemic phenomena caused by congestion that are almost 100% likely to occur in the system under consideration, namely the road traffic infrastructure. In addition to the process from creeping accommodation to risk transition, we also observe here a societal accommodation to road traffic risk itself, which has become a naturalized facet of (inter-)urban mobility.

3.2 | Digital massification and data congestion

In the context of digital massification and data congestion, instead of cars we think of data packets that can be prevented from reaching their destination in a timely manner. This can cause direct and secondary damage at the system level if critical services depend on them. The IoT can be seen as an ever-expanding network platform that enables connectivity and data transfer in smart cities between disparate and heterogeneous devices. Sensor nodes are used for any type of monitoring and measurement, such as in homes, industry, public spaces, and healthcare, to enable smart automation and promote forecasting capabilities (Sharma et al., 2019; Verma & Kumar, 2020). According to a study by Ericsson, the total number of internet-connected devices might exceed 24 billion by 2050 (Khanh et al., 2022).

The steady increase in market participants, consumers, and IoT devices in smart cities generates ever-growing amounts of data and is also accompanied by an increase in data-intensive applications. Digital massification and the risk of societal accommodation to data congestion in smart cities are part of an ongoing historical evolution of constantly increasing demands on data volume, transmission, and technological innovation within ultimately finite physical boundaries. Our historical perspective reveals that avoiding and controlling data congestion in digital networks has been a major concern since the first series of congestion collapses on the internet in October 1986 (Jacobson, 1988) and the rise of congestion control algorithms in the early 1990s (Yang & Reddy, 1995). Thirty-five years later, the problem persists, though at a higher level. Today, network engineers attempt to calculate the tolerable maximum number of devices for stable networks (El Soussi et al., 2018), pointing out that the expected increase in IoT devices may lead to severe congestion and even carry a high risk of congestion collapse (Bouzouita et al., 2016). In particular for critical IoT applications where on-time delivery of data is crucial, there is a "high possibility of congestion in the network […] which can cause delay and packet drop when left unnoticed" (Pushpa Mettilsha et al., 2021, p. 5229).

Similar to the expansion of the road traffic system, the continuous increase in bandwidth, processing capacity, and other technical innovations has expanded the physical limits of volume and speed in data transmission: from fiber-optic communication first installed in Germany in 1993 and soon called "Datenautobahn" (data highway) to current 5G and future 6G wireless technologies. However, even the latest technological innovations face problems of physical limitations, for example, when "the limited buffer space on the commodity switches becomes the critical resource" (Xu et al., 2019, p. 1911), and they still suffer from latencies and congestions, for example, due to physical blockage and misalignment of signals (Poorzare & Augé, 2020, p. 176395). While the analogical reasoning should not be overused, there are obvious similarities here both between capacity increases on "highways" for vehicles and for data packets and between their impairment by limited traffic flow on feeder roads or limited data packet processing at hardware nodes, such as commodity switches.

This is particularly relevant for all latency-sensitive tasks and services in smart cities (ultra-reliable and low-latency communications, URLLC), for example, critical applications in intelligent transportation, remote healthcare, or other real-time services that must not suffer any disturbance, delay, or congestion (Lorincz et al., 2021, pp. 28–29; Yaqoob et al., 2020). Recent trends in network engineering toward improvements in packet scheduling algorithms and protocols to meet the requirements of large-scale IoT systems for smart cities underscore the need to address congestion-related issues in smart cities (Fatemidokht et al., 2021; Qiu et al., 2018). Furthermore, edge computing technologies for smart cities (Khan et al., 2020) and for the IoT (W. Yu, Liang, et al., 2018) are currently expected to contribute to solving latency and congestion issues in cloud-based networks, where platform flooding by large amounts of data due to increasing smart city user requests may lead to the "crash of the entire system" (J. Yu, Fu, et al., 2018, p. 852). Priority queuing may avoid the most dramatic effects of data congestion by guaranteeing "the stability of critical packet queues while allowing regular traffic to be throttled" (Agaskar, 2018, p. 130). However, this raises the issue of "[f]airness […] as one of the main problems" (Lorincz et al., 2021, p. 33) in data transmission. This again points to the incremental increase in inconveniences and comfort losses for low-priority users.

A prominent example of URLLC-dependent critical urban services threatened by data congestion are intelligent transport systems for smart cities. These systems require the highest level of service reliability but are particularly vulnerable to latency and congestion in critical data transmission due to the high data rate and bulky nature of data from video-based traffic monitoring (Rashid & Rehmani, 2016, p. 2020). Moreover, network security computing increases wireless channel occupancy and end-to-end communication delay, particularly in high-density traffic scenarios (Ahmed & Rani, 2018, p. 2). Therefore, the challenge for engineers is to "reduce the chaos of sharing and processing a huge amount of data in a timely manner that may otherwise cause a massive channel load and congested network" (Kuru, 2021, p. 6583). Another example is the so-called Tactile Internet, which aims to transmit a sense of touch over the internet for applications in smart cities, such as in the domains of telemedicine, healthcare, education, transportation, or manufacturing. Just like intelligent transport systems, the Tactile Internet requires particularly low latency, in the range of 1 ms, and high bandwidth, of the order of gigabytes per second, to function reliably (Fettweis, 2014; Van Den Berg et al., 2017). Intelligent transport systems and the Tactile Internet are only two of many examples showing that, in addition to network capacity, low latency has become an important quality-of-service parameter for smart cities.

Thus, in general, data are sent in packets, and avoiding delays at any node or edge is of utmost priority to ensure high quality of service and minimize end-to-end latency so that, for example, haptic systems for industry or entertainment run stably. Major reasons for packet flow delay can be the size of the packets (propagation or transmission delay), the processing time of packet headers (processing delay), or queuing delays, that is, the time a packet has to wait in a queue before it is transmitted further (Turkovic et al., 2018). In contrast to propagation and transmission delays, processing and queuing delays depend in particular on the amount of traffic, that is, the number of market participants, consumers, and IoT devices connected to the internet (Turkovic et al., 2018). In other words, queuing delays occur when a network node attempts to forward more data than the outgoing link can handle. Common transport protocols such as Transmission Control Protocol detect the congestion at the sending node and change the transmission rate accordingly. The global COVID-19 pandemic exemplified how, under curfew, activities converge and shift from non-digital to digital, affecting internet traffic and platforms' performance in data transmission for professional or entertainment purposes, which can lead to temporary congestion and service interruptions (Feldmann et al., 2020).

The risk of data traffic congestion has been recognized, and much research has been done on improving queue management, network congestion detection, congestion control policies, and technologies in general to help reduce internet latency (Briscoe et al., 2016; de Morais et al., 2022; Mishra et al., 2018; Turkovic et al., 2018; Verma & Kumar, 2020; Xia et al., 2021). However, while scientists and engineers have long been concerned with how to avoid and resolve data traffic congestion, smart cities and the IoT pose new technical challenges due to the enormous heterogeneity of devices which require a multitude of different management policies for data transmission (Mishra et al., 2018, p. 445). The heterogeneous nature of the IoT in smart cities therefore requires continuous improvement of hardware, software, and protocols to ensure timely data transmission at all network levels from LoRaWAN to 5G (Habibzadeh et al., 2018).

Besides obvious similarities between massification in road traffic and data traffic, it is also important to consider limitations of analogical reasoning (Ravn, 2011, pp. 718–720), and akin to methodological issues in the comparative method, analogy needs to consider both "similarities *and* differences" (Handler, 2009, emphasis in the original). For example, while traffic jams lead to critical side effects discussed above, an increase in the number of vehicles per mile and the consequent decrease of traffic flow may actually lead to a falling rate of fatal traffic accidents due to reduced speed (Farmer, 2017), this degressive functional relationship is certainly not mirrored in the analogy where increasing data traffic does not lead to risk reduction in any sense. Second, traffic increase is subject to at least some demographic limitations in terms of the legal age for holding a drivers' license, which is different from the potentially unbounded increase of data producing IoT applications and users whose data packet transmissions may overload finite physical infrastructures. This difference, however, supports our argument for an impending threat of digital massification and data congestion.

We are currently in a comparatively early phase of digital massification in which delays, congestion, latency, and the associated time losses are already being experienced and society is increasingly naturalizing such negative side effects. At the same time, accommodation phenomena are already apparent in the form of routinely accepted and tolerated delays, especially in the leisure sector, but we cannot yet speak of real risks. This phase resembles the phase of early traffic jams in the road traffic system, when massification and the eventual risk transition had not yet entered societal awareness. Unlike the road traffic system, in the data traffic system there is in principal neither a minimum limitation on the number of market participants, consumers, and IoT devices by user licenses or technical inspection authorities nor a minimum limitation on the number of devices by quality control equivalent to the national technical inspection authority for road vehicles. With increasing digitalization and the expected continued increase in market participants, consumers, and IoT devices, the risk transition in dense and highly intertwined critical supply systems thus seems to be only a matter of time and is the subject of the next section.

4 | DISCUSSION: RISK EVOLUTION, RISK ACCOMODATION, AND RISK TRANSITION IN SMART CITIES

As outlined in the previous section, a long-term perspective on the road traffic system reveals the unfolding drama of massification including creeping societal accommodation to emerging congestion-related discomfort and eventually transition to substantial systemic risks, for example, in terms of economic and health impacts. Our historical and relational analogy has suggested that a similar risk evolution is already in the making through an uncontrolled increase in market participants, consumers, and IoT devices within physically finite critical infrastructures of smart cities. Against this background, it is even more important to note that massification as a risk driver in general, and digital massification in the context of smart cities in particular, has not yet been systematically addressed in the literature (Shayan et al., 2020). Since digital infrastructures themselves form the backbone of complex and highly interconnected critical infrastructure systems in future smart cities, we can classify digital massification as one among a number of drivers of systemic risk (Helbing, 2012).

The creeping societal accommodation to data congestion-induced delays or interruptions, which initially occurred primarily in the leisure and entertainment sectors, conditions a lack of attention to a pending risk transition. We wish to emphasize the significance of such a transition by pointing to the fact that smart critical utility services, with all the social consequences of potential failure, evolve within a technical system of information and communication infrastructures that is physically finite. In the context of digitalized urban critical infrastructures that rely on uninterrupted data flow, data traffic congestion is undoubtedly a future threat to cities, but one that has not entered substantial societal awareness to date. In the following, we therefore address the expected dramatic increase in market participants, consumers, and IoT devices and describe how critical urban services will change and how digital massification will potentially lead to risk transition over time.

4.1 | Smart city and critical functions

We have already pointed to the social and technical dynamics of digital massification as a potential driver of systemic risk in smart cities in terms of increased data traffic congestion and associated inconveniences or comfort losses. These considerations seem even more relevant in light of the prevalent visions for smart city development in the near future: Leading smart city corporations state that smart city technology will "address potential problems before they occur" by "making the invisible visible" (Harrison & Abbott Donnelly, 2011, p. 8) through real-time monitoring of the "smart urban metabolism" (Shahrokni et al., 2015). The computational capacities and databases of such visions rely on data collection through ubiquitously placed stationary sensors as well as mobile sensors carried in the devices and bodies of "cybernetic citizens" (Zandbergen & Uitermark, 2019), on massive expansion and continuous innovation of urban information and communication technologies, on algorithmic data analysis in smart urban operations centers, and on decision-making procedures based on machine learning and artificial intelligence.

The massive increase in data usage and data dependency of market participants, consumers, and IoT devices in smart cities is already evident. The digitalization of urban infrastructures, services, and everyday behaviors is an omnipresent phenomenon driven by self-reinforcing dynamics, since IoT interconnectivity and user reliance on smart phones and other smart devices to access digital services creates ever-increasing dependencies on data flows (Alba et al., 2017; Karnouskos et al., 2012; Longo et al., 2018; Shafique et al., 2020). Industry 4.0 is driving data traffic in production and business. In addition, the roll-out of smart meters for households is opening the door to future smart homes, where the IoT could potentially comprise all existing and yet-to-be-invented household item.

However, the situation is particularly sensitive given the general increase in data traffic, as more and more critical infrastructures are being digitized and automated, leading to sociotechnical problems arising from their digital convergence (Büscher et al., 2020). The non-functioning critical infrastructures, considered subsystems of socioeconomic systems such as smart cities (Haggag et al., 2020), directly impact basic services and welfare (Ouyang, 2014) and have transboundary ripple effects in the urban critical infrastructure system (Renn et al., 2020) and beyond. Critical infrastructures include, among others, the energy grid, the transportation system, water supply, healthcare and emergency services, as well as the banking and financial system. Critical infrastructures can be interconnected and may be mutually dependent or interdependent. The example of smart grids illustrates the interdependence of the power grid and information and communication technologies infrastructure, which is considered a dual power and data infrastructure: The failure of a node in one subsystem causes cascading failures in the same or in the other subsystem, and so forth (Buldyrev et al., 2010; Zio & Sansavini, 2011). Although we are not necessarily dealing here with direct interdependencies between infrastructures but simply with dependencies on an information and communication technologies network, the smart grid example shows that critical infrastructures that depend on information and communication technologies infrastructures are potentially more vulnerable (Buldyrev et al., 2010).

4.2 | Creeping accommodation: Time losses and systemic risk transition

The historical and relational analogy has led us to consider whether a risk transition, such as that caused by congestion in the vehicular road traffic system, is likely to occur in the emerging sociotechnical critical subsystems of smart cities, which rely on uninterrupted data traffic. As we have seen in the previous sections, critical infrastructures in smart cities deserve special attention also because a further increase in delays and failures poses risks to urban safety and supply.

Although fully fledged smart cities are still an urban planning vision in most countries around the world, many cities have already entered the era of digital massification, encountering a crescendo of problems related to data congestion and delays. Citizens are increasingly familiar with such delays, so far primarily in the spheres of leisure and entertainment, and have learned and are still learning to live with them—the process of accommodating inconveniences, a feature of digital massification, has thus been underway for years. However, we cannot yet speak of systemic risks related to data traffic congestion. But with the increasing digitalization of critical supply systems and a lack of societal awareness due to a creeping process of accommodation to delays and loss of time in data-driven services, we can anticipate by historical analogy that data congestion will have noticeable impacts on critical services in the coming years or decades if the number of market participants, consumers, and IoT devices continues to grow.

In the process, the probability of data congestion continues to increase, with data congestion itself seen as a trigger event having impacts of systemic scope: In addition to immediate and direct sectoral risks, transboundary ripple effects and damages in urban and regional contexts arise due to the aforementioned interdependencies and convergences. Risks result from congestion-related latencies or failures of data-intensive applications such as intelligent transport systems or the Tactile Internet and may cause immediate economic damages, injuries in the health sector, or even fatalities in traffic and other sectors. Digital massification, understood as a long-term process over many decades, particularly affects critical service infrastructure and must therefore be explicitly named as a driver of systemic risk. In our conclusion, we will therefore urge that digital massification in the context of smart city planning and development finally be moved out of the blind spot of long-term governance.

5 | CONCLUSION: RESPONDING TO SYSTEMIC RISK DRIVERS

In systems with high levels of dynamic complexity due to a high degree of technical and sociotechnical interconnectedness and interdependencies, both endogenous and exogenous, random events can be seen as triggers of adverse systemic phenomena (Helbing, 2012). In this sense, the threat of digital over-complexity, as in the case of smart grids (Parag & Sovacool, 2016), can be seen as a driver of systemic risk in smart cities and should be analyzed and understood in its own right in order to draw conclusions about minimum levels of required complexity (Buldyrev et al., 2010). In addition to complexity as an aspect of manifest systemic risk, in this article we have identified and defined digital massification as a driver of systemic risk with regard to complex and digitalized critical infrastructure systems in future smart cities. We have argued that long-term risk evolution, as a characteristic of massification, is likely to escape societal and policy awareness due to its incremental nature and society's concomitant accommodation to gradually growing inconveniences.

As mentioned above, the increase in data traffic congestion is a foreseeable and actual deterministic development for smart cities given the finiteness of digital infrastructures within the context of an almost completely liberal market that in principle allows uncontrolled multiplication and increase of market participants, consumers, and IoT devices. Cultural dynamics such as the acceleration of urban life rhythms (Vostal, 2019) can further increase the number of data producing human–machine or machine–machine interactions over a given period of time. It should be noted that this free-market development is accompanied by a significant backlog of regulation by governments or local urban authorities (Dameri & Benevolo, 2016; Russo et al., 2016). Digital massification thus gains an actual deterministic dynamic toward risk transition, not only because the multiplication and increase of market participants, consumers, and IoT devices will be difficult to contain under free-market conditions but also because digital massification as a systemic risk driver itself has so far largely escaped the attention of society and policymakers. Under these circumstances, the problem is unlikely to be addressed through regulation or mitigation and adaptation measures before risk transition occurs. In retrospect and as a reference to "learning from history," the massive negative consequences of road traffic congestion should have been classified as a driver of systemic risk early on to prepare societal response for the phase when comfort losses turn into distinct health and economic impacts.

While systemic risks driven by increasing complexity may possibly be responded to in real time by technical solutions for dealing with such higher levels of complexity, increased systemic risks from increased congestion due to massification occur within physically limited infrastructures whose expansion can only be realized in the long term. For tautological reasons, adaptation by expansion nevertheless cannot solve the problem of continuing massification since it can only shift physical infrastructure to another level of finiteness, leading only to delayed congestion effects. This underlines all the more the urgency of making social and non-digital adaptive and anticipatory capacities an integral part of resilient smart city planning. At the level of urban policy and governance, this includes citizen perspectives, local knowledge, and the provision of means for self-organization (Buzzanell, 2018, p. 15), that is, at the neighborhood level in the 15-min city (Moreno et al., 2021, p. 15). We therefore conclude with a prospective outlook on how increased attention to systemic risk drivers may combine with avant-garde risk policy for smart cities.

Comprehensive current research on smart city risks promotes the inclusion of technological, organizational, and environmental levels, to which cultural dimensions of risk could be added. The proposal of Ullah et al. (2021) to seek iterative ways in citizen–government collaboration to identify, analyze, evaluate, monitor, and respond to risks is consistent with our own analysis of incremental risk evolution toward risk transition. It would be important, though, to focus these efforts not only on systemic risks themselves but also on systemic risk drivers, such as massification combined with increasing complexity, in order to achieve long-term smart city governance.

Raising awareness for systemic risk drivers, such as massification, could be achieved through innovative tools and methods for developing concrete long-term policy options in the face of future uncertainty (Muñoz-Erickson et al., 2021, p. 169). Societal sensitivity to data-related risks is a prerequisite for building resilient smart cities, just as sensitivity to local water conditions helps building water-resilient cities (Fields & Renne, 2021). This entails sensitivity not only to technical data traffic infrastructure but also to legal and ethical aspects of data mining, propriety, or storage, for which some awareness has already been raised. With a view to interdependent and digitalized critical services in smart cities, data sensitivity also means raising awareness of what happens when data traffic fails.

ACKNOWLEDGMENTS

We are grateful to both anonymous peer reviewers for their comments that helped enhancing the quality of the manuscript.

Open Access funding enabled and organized by Projekt DEAL.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

FUNDING INFORMATION

This research article has not received any funding.

ORCID

Sadeeb Simon Ottenburger https://orcid.org/0000-0001-9790-5444

REFERENCES

Agaskar, M. P. (2018). *Architectural constructs for time-critical networking in the smart city* [Thesis]. Institute of Technology, Cambridge, MA, USA. https://dspace.mit.edu/handle/1721.1/120377

Ahmed, S. H., & Rani, S. (2018). A hybrid approach, smart street use case and future aspects for Internet of Things in smart cities. *Future Generation Computer Systems*, *79*, 941–951. https://doi.org/10.1016/j.future.2017.08.054

Alba, E., Chicano, F., & Luque, G. (Eds.). (2017). *Smart cities* (vol. 10268). Springer International Publishing. https://doi.org/10.1007/978-3-319-59513-9

Bak, P. (1997). *How nature works: The science of self-organized criticality*. University Press.

Barrowman, N. (2014). Correlation, causation, and confusion. *The New Atlantis*, *43*, 23–44.

Bierth, C., Irresberger, F., & Weiß, G. N. F. (2015). Systemic risk of insurers around the globe. *Journal of Banking & Finance*, *55*, 232–245. https://doi.org/10.1016/j.jbankfin.2015.02.014

Bouzouita, M., Hadjadj-Aoult, Y., Zangar, N., & Tabbane, S. (2016). On the risk of congestion collapse in heavily congested M2M networks. *2016 International Symposium on Networks, Computers and Communications (ISNCC)*, Yasmine Hammamet, Tunisia. https://doi.org/10.1109/ISNCC.2016.7746063

Briscoe, B., Brunstrom, A., Petlund, A., Hayes, D., Ros, D., Tsang, I.-J., Gjessing, S., Fairhurst, G., Griwodz, C., & Welzl, M. (2016). Reducing internet latency: A survey of techniques and their merits. *IEEE Communications Surveys & Tutorials*, *18*(3), 2149–2196. https://doi.org/10.1109/COMST.2014.2375213

Buldyrev, S. V., Parshani, R., Paul, G., Stanley, H. E., & Havlin, S. (2010). Catastrophic cascade of failures in interdependent networks. *Nature*, *464*(7291), Article7291. https://doi.org/10.1038/nature08932

Büscher, C., Ornetzeder, M., & Droste-Franke, B. (2020). Converging infrastructures: Amplified socio-technical problems. *TATuP - Zeitschrift Für Technikfolgenabschätzung in Theorie Und Praxis*, *29*(2), 10–51. https://doi.org/10.14512/tatup.29.2.10

Buzzanell, P. M. (2018). Organizing resilience as adaptive-transformational tensions. *Journal of Applied Communication Research*, *46*(1), 14–18. https://doi.org/10.1080/00909882.2018.1426711

Connolly, D., Lund, H., & Mathiesen, B. V. (2016). Smart energy Europe: The technical and economic impact of one potential 100% renewable energy scenario for the European Union. *Renewable and Sustainable*

Energy Reviews, *60*, 1634–1653. https://doi.org/10.1016/j.rser.2016.02.025

Dameri, R. P., & Benevolo, C. (2016). Governing smart cities: An empirical analysis. *Social Science Computer Review*, *34*(6), 693–707. https://doi.org/10.1177/0894439315611093

de Morais, W. G., Santos, C. E. M., & Pedroso, C. M. (2022). Application of active queue management for real-time adaptive video streaming. *Telecommunication Systems*, *79*(2), 261–270. https://doi.org/10.1007/s11235-021-00848-0

El Soussi, M., Zand, P., Pasveer, F., & Dolmans, G. (2018). Evaluating the performance of eMTC and NB-IoT for smart city applications. *2018 IEEE International Conference on Communications (ICC)*, Kansas City, MO, USA. https://doi.org/10.1109/ICC.2018.8422799

Farmer, C. M. (2017). Relationship of traffic fatality rates to maximum state speed limits. *Traffic Injury Prevention*, *18*(4), 375–380. https://doi.org/10.1080/15389588.2016.1213821

Fatemidokht, H., Rafsanjani, M. K., Gupta, B. B., & Hsu, C.-H. (2021). Efficient and secure routing protocol based on artificial intelligence algorithms with UAV-assisted for vehicular ad hoc networks in intelligent transportation systems. *IEEE Transactions on Intelligent Transportation Systems*, *22*(7), 4757–4769. https://doi.org/10.1109/TITS.2020.3041746

Feldmann, A., Gasser, O., Lichtblau, F., Pujol, E., Poese, I., Dietzel, C., Wagner, D., Wichtlhuber, M., Tapiador, J., Vallina-Rodriguez, N., Hohlfeld, O., & Smaragdakis, G. (2020). The lockdown effect: Implications of the COVID-19 pandemic on internet traffic. *Proceedings of the ACM Internet Measurement Conference*, New York, NY, USA. https://doi.org/10.1145/3419394.3423658

Fettweis, G. P. (2014). The tactile internet: Applications and challenges. *IEEE Vehicular Technology Magazine*, *9*(1), 64–70. https://doi.org/10.1109/MVT.2013.2295069

Fields, B., & Renne, J. L. (2021). *Adaptation urbanism and resilient communities: Transforming streets to address climate change*. Routledge.

Flick, D. L. (1991). Analogy and metaphor: Tools for understanding inquiry science methods. *Journal of Science Teacher Education*, *2*(3), 61–66. https://doi.org/10.1007/BF02629748

Fox, W. S., & Wince, M. H. (1975). Musical taste cultures and taste publics. *Youth & Society*, *7*(2), 198–224. https://doi.org/10.1177/0044118x7500700205

Habibzadeh, H., Soyata, T., Kantarci, B., Boukerche, A., & Kaptan, C. (2018). Sensing, communication and security planes: A new challenge for a smart city system design. *Computer Networks*, *144*, 163–200. https://doi.org/10.1016/j.comnet.2018.08.001

Haggag, M., Ezzeldin, M., El-Dakhakhni, W., & Hassini, E. (2020). Resilient cities critical infrastructure interdependence: A meta-research. *Sustainable and Resilient Infrastructure*, *7*, 291–312. https://doi.org/10.1080/23789689.2020.1795571

Halden, R. U., Rolsky, C., & Khan, F. R. (2021). Time: A key driver of uncertainty when assessing the risk of environmental plastics to human health. *Environmental Science & Technology*, *55*, 12766–12769. https://doi.org/10.1021/acs.est.1c02580

Handler, R. (2009). The uses of incommensurability in anthropology. *New Literary History*, *40*(3), 627–647. https://doi.org/10.1353/nlh.0.0101

Harrison, C., & Abbott Donnelly, I. (2011). A theory of smart cities. *Proceedings of the 55th Annual Meeting of the International Society for the Systems Sciences*, Hull, UK. http://journals.isss.org/index.php/proceedings55th/article/view/1703/572>

Haubrich, J. G., Lo, A. W., & National Bureau of Economic Research (Eds.). (2013). *Quantifying systemic risk*. Univ. of Chicago Press.

Hautsch, N., Schaumburg, J., & Schienle, M. (2015). Financial network systemic risk contributions. *Review of Finance*, *19*(2), 685–738. https://doi.org/10.1093/rof/rfu010

Helbing, D. (2012). Systemic risks in society and economics. In D. Helbing (Ed.), *Social self-organization* (pp. 261–284). Springer. https://doi.org/10.1007/978-3-642-24004-1_14

Helbing, D. (2013). Globally networked risks and how to respond. *Nature*, *497*(7447), Article7447. https://doi.org/10.1038/nature12047

Jacobson, V. (1988). Congestion avoidance and control. *ACM SIGCOMM Computer Communication Review*, *18*(4), 314–329. https://doi.org/10.1145/52325.52356

Jayasooriya, S. A. C. S., & Bandara, Y. M. M. S. (2017). Measuring the economic costs of traffic congestion. *2017 Moratuwa Engineering Research Conference (MERCon)*, Moratuwa, Sri Lanka. https://doi.org/10.1109/MERCon.2017.7980471

Karnouskos, S., Da Silva, P. G., & Ilic, D. (2012). Energy services for the smart grid city. *2012 6th IEEE International Conference on Digital Ecosystems and Technologies (DEST)*, Campione d'Italia, Italy. https://doi.org/10.1109/DEST.2012.6227925

Khan, L. U., Yaqoob, I., Tran, N. H., Kazmi, S. M. A., Dang, T. N., & Hong, C. S. (2020). Edge-computing-enabled smart cities: A comprehensive survey. *IEEE Internet of Things Journal*, *7*(10), 10200–10232. https://doi.org/10.1109/JIOT.2020.2987070

Khanh, Q. V., Hoai, N. V., Manh, L. D., Le, A. N., & Jeon, G. (2022). Wireless communication technologies for IoT in 5G: Vision, applications, and challenges. *Wireless Communications and Mobile Computing*, *2022*, 1–12. https://doi.org/10.1155/2022/3229294

Kraftfahrt-Bundesamt. (2022). Kraftfahrt-Bundesamt—Fahrzeugklassen und Aufbauarten—Bestand nach Fahrzeugklassen und Aufbauarten. https://www.kba.de/DE/Statistik/Fahrzeuge/Bestand/FahrzeugklassenAufbauarten/2022/b_fzkl_zeitreihen.html?nn=3524712&fromStatistic=3524712&yearFilter=2022&fromStatistic=3524712&yearFilter=2022

Kuru, K. (2021). Planning the future of smart cities with swarms of fully autonomous unmanned aerial vehicles using a novel framework. *IEEE Access*, *9*, 6571–6595. https://doi.org/10.1109/ACCESS.2020.3049094

Levy, J. I., Buonocore, J. J., & von Stackelberg, K. (2010). Evaluation of the public health impacts of traffic congestion: A health risk assessment. *Environmental Health*, *9*(1), 65. https://doi.org/10.1186/1476-069X-9-65

Liu, J., Jin, F., Xie, Q., & Skitmore, M. (2017). Improving risk assessment in financial feasibility of international engineering projects: A risk driver perspective. *International Journal of Project Management*, *35*(2), 204–211. https://doi.org/10.1016/j.ijproman.2016.11.004

Longo, A., Zappatore, M., Villari, M., Rana, O., Bruneo, D., Ranjan, R., Fazio, M., & Massonet, P. (Eds.). (2018). *Cloud infrastructures, services, and IoT systems for smart cities* (vol. 189). Springer International Publishing. https://doi.org/10.1007/978-3-319-67636-4

Lorincz, J., Klarin, Z., & Ožegović, J. (2021). A comprehensive overview of TCP congestion control in 5G networks: Research challenges and future perspectives. *Sensors*, *21*(13), 4510. https://doi.org/10.3390/s21134510

Loveridge, D. (2009). *Foresight: The art and science of anticipating the future*. Routledge.

Mishra, N., Verma, L. P., Srivastava, P. K., & Gupta, A. (2018). An analysis of IoT congestion control policies. *Procedia Computer Science*, *132*, 444–450. https://doi.org/10.1016/j.procs.2018.05.158

Moheet, A., & Seaquist, E. R. (2013). Hypoglycemia as a driver of cardiovascular risk in diabetes. *Current Atherosclerosis Reports*, *15*(9), 351. https://doi.org/10.1007/s11883-013-0351-7

Moore, M., Gould, P., & Keary, B. S. (2003). Global urbanization and impact on health. *International Journal of Hygiene and Environmental Health*, *206*(4–5), 269–278. https://doi.org/10.1078/1438-4639-00223

Moreno, C., Allam, Z., Chabaud, D., Gall, C., & Pratlong, F. (2021). Introducing the "15-Minute city": Sustainability, resilience and place identity in future post-pandemic cities. *Smart Cities*, *4*(1), 93–111. https://doi.org/10.3390/smartcities4010006

Muñoz-Erickson, T. A., Selkirk, K., Hobbins, R., Miller, C., Feagan, M., Iwaniec, D. M., Miller, T. R., & Cook, E. M. (2021). Anticipatory resilience bringing back the future into urban planning and knowledge systems. In Z. A. Hamstead, D. M. Iwaniec, T. McPhearson, M. Berbés-Blázquez, E. M. Cook, & T. A. Muñoz-Erickson (Eds.), *Resilient urban futures* (pp. 159–172). Springer International Publishing. https://doi.org/10.1007/978-3-030-63131-4_11

Nelson, S. C., & Katzenstein, P. J. (2014). Uncertainty, risk, and the financial crisis of 2008. *International Organization*, *68*(2), 361–392.

Ouyang, M. (2014). Review on modeling and simulation of interdependent critical infrastructure systems. *Reliability Engineering & System Safety*, *121*, 43–60. https://doi.org/10.1016/j.ress.2013.06.040

Parag, Y., & Sovacool, B. K. (2016). Electricity market design for the prosumer era. *Nature Energy*, *1*(4), 16032. https://doi.org/10.1038/nenergy.2016.32

Poorzare, R., & Augé, A. C. (2020). Challenges on the way of implementing TCP over 5G networks. *IEEE Access*, *8*, 176393–176415. https://doi.org/10.1109/ACCESS.2020.3026540

Pushpa Mettilsha, J., Sandhya, M. K., & Murugan, K. (2021). RPR: Reliable path routing protocol to mitigate congestion in critical IoT applications. *Wireless Networks*, *27*(8), 5229–5243. https://doi.org/10.1007/s11276-021-02805-w

Qiu, T., Zheng, K., Han, M., Chen, C. L. P., & Xu, M. (2018). A data-emergency-aware scheduling scheme for Internet of Things in smart cities. *IEEE Transactions on Industrial Informatics*, *14*(5), 2042–2051. https://doi.org/10.1109/TII.2017.2763971

Rashid, B., & Rehmani, M. H. (2016). Applications of wireless sensor networks for urban areas: A survey. *Journal of Network and Computer Applications*, *60*, 192–219. https://doi.org/10.1016/j.jnca.2015.09.008

Ravn, M. (2011). Ethnographic analogy from the pacific: Just as analogical as any other analogy. *World Archaeology*, *43*(4), 716–725.

Renn, O., Laubichler, M., Lucas, K., Kröger, W., Schanze, J., Scholz, R. W., & Schweizer, P. (2020). Systemic risks from different perspectives. *Risk Analysis*, *42*, 1902–1920. https://doi.org/10.1111/risa.13657

Russo, F., Rindone, C., & Panuccio, P. (2016). European plans for the smart city: From theories and rules to logistics test case. *European Planning Studies*, *24*(9), 1709–1726. https://doi.org/10.1080/09654313.2016.1182120

Shafique, K., Khawaja, B. A., Sabir, F., Qazi, S., & Mustaqim, M. (2020). Internet of Things (IoT) for next-generation smart systems: A review of current challenges, future trends and prospects for emerging 5G-IoT scenarios. *IEEE Access*, *8*, 23022–23040. https://doi.org/10.1109/ACCESS.2020.2970118

Shahrokni, H., Lazarevic, D., & Brandt, N. (2015). Smart urban metabolism: Towards a real-time understanding of the energy and material flows of a city and its citizens. *Journal of Urban Technology*, *22*(1), 65–86. https://doi.org/10.1080/10630732.2014.954899

Sharma, V. K., Verma, L. P., & Kumar, M. (2019). CL-ADSP: Cross-layer adaptive data scheduling policy in mobile ad-hoc networks. *Future Generation Computer Systems*, *97*, 530–563. https://doi.org/10.1016/j.future.2019.03.013

Shayan, S., Kim, K. P., Ma, T., & Nguyen, T. H. D. (2020). The first two decades of smart city research from a risk perspective. *Sustainability*, *12*(21), 9280. https://doi.org/10.3390/su12219280

Statista. (2022a). Autobahnen in Deutschland—Gesamte Staulänge 2021. https://de.statista.com/statistik/daten/studie/200201/umfrage/gesamte-staulaenge-auf-autobahnen-in-deutschland/

Statista. (2022b). Autobahnen—Netzlänge in Europa. https://de.statista.com/statistik/daten/studie/154113/umfrage/netzlaenge-der-autobahnen-in-europaeischen-laendern/

Statista. (2022c). Staumeldungen in Deutschland bis 2021. https://de.statista.com/statistik/daten/studie/169948/umfrage/anzahl-der-staumeldungen-in-deutschland/

Statista. (2022d). Staustunden auf Autobahnen. https://de.statista.com/statistik/daten/studie/508860/umfrage/staustunden-auf-deutschen-autobahnen/

Sterman, J. (2000). *Business dynamics: Systems thinking and modeling for a complex world*. Irwin/McGraw-Hill.

Syrovatka, J. (2000). Analogy and understanding. *Theoria: An International Journal for Theory, History and Foundations of Science*, *15*(339), 435–450.

Tacconelli, E. (2009). Antimicrobial use: Risk driver of multidrug resistant microorganisms in healthcare settings. *Current Opinion in Infectious Diseases*, *22*(4), 352–358. https://doi.org/10.1097/QCO.0b013e32832d52e0

Tarashev, N. A., Borio, C. E. V., & Tsatsaronis, K. (2010). Attributing systemic risk to individual institutions. *SSRN Electronic Journal*, 38. https://doi.org/10.2139/ssrn.1631761

Turkovic, B., Kuipers, F., van Adrichem, N., & Langendoen, K. (2018). Fast network congestion detection and avoidance using P4. *Proceedings of the 2018 Workshop on Networking for Emerging Applications and Technologies*, Budapest, Hungary. https://doi.org/10.1145/3229574.3229581

Ullah, F., Qayyum, S., Thaheem, M. J., Al-Turjman, F., & Sepasgozar, S. M. E. (2021). Risk management in sustainable smart cities governance: A TOE framework. *Technological Forecasting and Social Change*, *167*, 120743. https://doi.org/10.1016/j.techfore.2021.120743

Van Den Berg, D., Glans, R., De Koning, D., Kuipers, F. A., Lugtenburg, J., Polachan, K., Venkata, P. T., Singh, C., Turkovic, B., & Van Wijk, B. (2017). Challenges in haptic communications over the Tactile Internet. *IEEE Access*, *5*, 23502–23518. https://doi.org/10.1109/ACCESS.2017.2764181

Verma, L. P., & Kumar, M. (2020). An IoT based congestion control algorithm. *Internet of Things*, *9*, 100157. https://doi.org/10.1016/j.iot.2019.100157

Vostal, F. (2019). Acceleration approximating science and technology studies: On Judy Wajcman's recent oeuvre. *Science, Technology, & Human Values*, *44*(4), 686–706. https://doi.org/10.1177/0162243919845140

Weisbrod, G., Vary, D., & Treyz, G. (2003). Measuring economic costs of urban traffic congestion to business. *Transportation Research Record: Journal of the Transportation Research Board*, *1839*(1), 98–106. https://doi.org/10.3141/1839-10

Weiß, G. N. F., Bostandzic, D., & Neumann, S. (2014). What factors drive systemic risk during international financial crises? *Journal of Banking & Finance*, *41*, 78–96. https://doi.org/10.1016/j.jbankfin.2014.01.001

Xia, Z., Xue, S., Wu, J., Chen, Y., Chen, J., & Wu, L. (2021). Deep reinforcement learning for smart city communication networks. *IEEE Transactions on Industrial Informatics*, *17*(6), 4188–4196. https://doi.org/10.1109/TII.2020.3006199

Xu, Y., Shukla, S., Guo, Z., Liu, S., Tam, A. S.-W., Xi, K., & Chao, H. J. (2019). RAPID: Avoiding TCP incast throughput collapse in public clouds with intelligent packet discarding. *IEEE Journal on Selected Areas in Communications*, *37*(8), 1911–1923. https://doi.org/10.1109/JSAC.2019.2927072

Yaqoob, I., Khan, L. U., Kazmi, S. M. A., Imran, M., Guizani, N., & Hong, C. S. (2020). Autonomous driving cars in smart cities: Recent advances, requirements, and challenges. *IEEE Network*, *34*(1), 174–181. https://doi.org/10.1109/MNET.2019.1900120>

Yang, C. Q., & Reddy, A. V. S. (1995). A taxonomy for congestion control algorithms in packet switching networks. *IEEE Network*, *9*(4), 34–45. https://doi.org/10.1109/65.397042

Yu, J., Fu, B., Cao, A., He, Z., & Wu, D. (2018). EdgeCNN: A hybrid architecture for agile learning of healthcare data from IoT devices. *2018 IEEE 24th International Conference on Parallel and Distributed Systems (ICPADS)*, Singapore. https://doi.org/10.1109/PADSW.2018.8644604

Yu, W., Liang, F., He, X., Hatcher, W. G., Lu, C., Lin, J., & Yang, X. (2018). A survey on the edge computing for the Internet of Things. *IEEE Access*, *6*, 6900–6919. https://doi.org/10.1109/ACCESS.2017.2778504

Zandbergen, D., & Uitermark, J. (2019). In search of the smart citizen: Republican and cybernetic citizenship in the smart city. *Urban Studies*, *57*(8), 1733–1748. https://doi.org/10.1177/0042098019847410

Zhang, K., & Batterman, S. (2013). Air pollution and health risks due to vehicle traffic. *Science of The Total Environment*, *450–451*, 307–316. https://doi.org/10.1016/j.scitotenv.2013.01.074

Zio, E., & Sansavini, G. (2011). Component criticality in failure cascade processes of network systems: Component criticality in failure cascade processes. *Risk Analysis*, *31*(8), 1196–1210. https://doi.org/10.1111/j.1539-6924.2011.01584.x

How to cite this article: Ottenburger, S. S., & Ufer, U. (2023). Smart cities at risk: Systemic risk drivers in the blind spot of long-term governance. *Risk Analysis*, 1–11. https://doi.org/10.1111/risa.14102