CREMA

Center for Research in Economics, Management and the Arts

Safety in Smart, Livable Cities: Acknowledging the Human Factor

Working Paper No. 2021-17

CREMA Südstrasse 11 CH - 8008 Zürich www.crema-research.ch

Safety in Smart, Livable Cities: Acknowledging the Human Factor

Steve J. Bickley[a,b], Alison Macintyre[b] and Benno Torgler[a,b,c]

Affiliations

[a] School of Economics and Finance, Queensland University of Technology, 2 George St, Brisbane QLD 4000, Australia

[b] Centre for Behavioural Economics, Society and Technology (BEST), 2 George St, Brisbane QLD 4000, Australia

[c] CREMA – Centre for Research in Economics, Management, and the Arts, Südstrasse 11, CH-8008 Zürich, Switzerland

Abstract

AI and Big Data provide opportunities and challenges with respect to how we achieve safety in livable smart cities. In this contribution, we look at set of aspects that are important at the city level; namely, how urban analytics and digital technologies can be used; how crime safety is influenced by predictive policing; how city planning and urban development can use real-time data; how complexity is connected to traffic safety; how AI offers opportunities for public health; and what are the societal implications of using, applying, or implementing new technologies. A core argument of the paper is the significance of acknowledging the 'human factor' when using smart technologies to design a safe and livable smart city.

Keywords

Artificial Intelligence, Big Data, Smart City, Sustainability, Human Factors

The growth of knowledge is one of the most irreversible forces known to mankind. It takes a catastrophe of very large dimensions to diminish the total stock of knowledge in the possession of man. Even in the rise and fall of great civilizations surprisingly little has been permanently lost, and much that was lost for a short time was easily regained. Hence there is no hope for ignorance or for a morality based on it. Once we tasted the fruit of the tree of knowledge, as the Biblical story illustrates so well, Eden is closed to us. We cannot go back to the childhood of our race any more than we can go back to our own childhood without disaster. Eden has been lost to us forever and an angel with a flaming sword stands guard at its gates. Therefore either we must wander hopelessly in the world or we must press forward to Zion. We must learn to master ourselves as we are learning to master nature.

Kenneth Boulding (1964, p.p. 24-25).

1. Introduction

People today are concentrated in cities as never before in the history of humanity. Cities function as hubs of opportunities, innovation, and creativity, along with social exchange and activities, offering ecosystems of chance and exploration. They benefit from systematic economies of scale with respect to infrastructure required (about 85 percent more material infrastructure with every doubling of city size), and the larger the cities, the more innovative social capital is created (West 2017). On the other hand, negative indicators of human social behavior also increase approximately to the same degree as positive indicators (West 2017). The good, the bad, and the ugly are all dimensions of the same city. Achieving a safe, healthy, and efficient society is a scientific and societal challenge that has been a concern since civilized societies emerged. However, centralized network solutions that allow for safe food and transportation, clean water, or commerce to flourish are becoming increasingly rare and obsolete (Pentland 2014). The promise of our future cities – in the form of smart cities and through the use of artificial intelligence (AI) – suggest wonderful opportunities but are also subject to challenges (cue opportunity) due to the major urban transformations required. The science of cities dates back to at least Aristotle, and is now experiencing a renaissance:

> Just within academia itself there is a dizzying array of separate departments, centers, and institutes representing a broad spectrum of alternative ways of perceiving cities: urban geography, urban economics, urban planning, urban studies, urbanomics, architectural studies, and many more, each with its own culture, paradigm, and agenda, though rarely interacting with one another. The

> situation is rapidly changing as new developments are being initiated, many stimulated by the advent of Big Data and the vision of smart cities, both somewhat naively touted as panaceas for solving all of our urban problems (West 2017, p. 270).

Daily interaction between humans, technology, and AI (i.e., intelligent systems and machines) is commonplace in modern life. Increasingly, AI is being used to augment and extend human decision-making capabilities (Metcalf et al. 2019), particularly in the workplace – and to a greater extent, society at large. On one hand, intelligent technologies can increase speed, consistency, and quality of process execution and production. On the other hand, human oversight and supervision can enable more flexible (Sabattini et al. 2018), adaptable, and resilient processes (Chiou and Lee 2016). Further, there are situations in which too much automation may increase complacency in human supervisors / operators (Baker and Keebler, 2017), suggesting a fine line between the benefits and costs of AI, particularly in safety-sensitive contexts. Clearly, it is necessary to analyze and understand complex human sociotechnical systems to capture the benefits that both agents (human and artificial) can offer in modern society.

In this paper, we argue that AI and Big Data solutions require consideration of the human component(s) / human factor(s) when successfully designing a smart livable city that flourishes and thrives in a sustainable manner. We begin by introducing the foundational relation between *urban analytics and digital technologies*, and their role in smart, livable cities. Next, we explore the implications and challenges of such technologies in the domains of *predictive policing*, *city planning and urban development*, *traffic safety*, and *public health*. Finally, we discuss the challenges and opportunities in the *use, application, and implementation of smart technologies* in smart, livable cities before summarizing our arguments in the concluding remarks.

2. Urban Analytics and Digital Technologies

The potential instrumentation of smart cities is welcomed by engineers and planners – as well as end users – for managing flows of energy, traffic, and general resources proactively in the most efficient manner, as well as reactively in response to shocks, pandemics, or natural disasters. For example, analyzing the difference in pre- and during pandemic energy use in Canada indicates a large variation in demand for resources (Abu-Rayash and Dincer 2020); advance knowledge of the extent of this divergence would allow planners to divert resources where they are able to best support people's needs. With the current rate of ecosystem destruction and biodiversity loss, and the escalating climate crisis, the requirement for better responses to changing resource needs in crises will only increase. AI and Big Data promise leaps and bounds in sustainability progress (Vinuesa et al. 2020) and nurturing sustainable innovation and entrepreneurship (Bickley et al. 2021), but may also trigger a range of non-insignificant ethical, safety, and technological challenges such as technological inequality, biased and/or ill-intentioned applications/developments, and mass power consumption.

Digital feedback technologies allow for dynamic reactions and responses not seen before, many of which require rethinking how we need to reinvent our societal system (Pentland 2014). Yet, smart cities need to still be human-friendly and organic cities, designed according to the realities of human behavior, which can be quite messy. The risk to our safety in over-instrumenting a smart city is that we create another situation of distorted incentives and interventions based on faulty, simplified assumptions about what is most efficient, that go against the complex collaborative ability of humans to form groups and spontaneously cooperate. Torgler, García-Valiñas, and Macintyre (2010) discuss how the wrong intervention in the wrong context (or, indeed, the right intervention in the wrong context) will potentially crowd out intrinsic motivation and produce iatrogenic effects well beyond the scope of the policy. They echo Ostrom's (2000) concern that policies based on assumptions about payoff structures of the rational egoists may have crowded out social norms that facilitate collective action, and this highlights a dangerous dark side to engineering or distorting human incentives based on a priori assumptions. If we make an error of judgement with AI on the same scale of the mistaken assumptions behind environmental policy, the risks are significant.

The benefit of smart cities and AI is that the evidence-based collection of information with Big Data can inform what those better conditions are, rather than designing based on assumptions made in advance. In turn, the observations can inform smaller interventions based on challenging social institutions and social norms where they are sticky in the negative sense, perpetuating oppression and exploitation or negative exclusion. The ability to harness such benefits beg the use of a guiding conceptual framework to the design and analysis of complex sociotechnical systems. Stowers et al. (2017) and Kerstholt et al. (2019) offer two such contributions.

3. Predictive Policing

Historically, urban studies have been a less quantitative area than other fields (West 2017). The accumulation of urban analytics has been applied at the city level to deal with aspects such as traffic data, crime statistics, or closed-circuit cameras to identify, for example, criminal activities or terrorist threats (Eagle and Greene 2014). However, mass surveillances can also be experienced as a threat by citizens (Helbing 2015). An overview of field experimental evidence indicates that surveillance cameras can reduce property crimes but concerns remain in regards to displacement effects (Alexandrie 2017). The use of specialized algorithms and real-time crime data provide the opportunity for frequent updates of crime maps and potentially influence safety by adjusting police locations before actual crimes occur (Eagle and Greene 2014). Thus, such dynamic geographical information can be very powerful for crime prevention and law enforcement. As Cohen et al. (2007) stress, "crime mapping based on near-real-time input of police reports has made the current picture for police more complete, integrating data from various officers, shifts, and neighborhoods" (p. 106). Two notable examples of this approach are Memphis' program Blue CRUSH (Criminal Reduction Utilizing Statistical History), and that of New York City, which has used computerized crime systems since 1994 (Compstat) (Eagle and Greene 2014). The use of Big Data to gather new information that guides more accurate forecasts of changes in crime was a good step forward from a safety perspective. Cohen et al. (2007), for example, developed and evaluated a crime-based leading indicator and spatial interactions as a way to forecast breaks in serious crime levels. One goal is to gather information on the smallest geographic areas possible (e.g., patrol districts in the US). It is a trade-off to get sufficient data volumes for such small units, which often requires aggregating crime data. Cohen et al. (2007) used 1.3 million individual crime incident data records for Pittsburgh, Pennsylvania over the period of 1991 to 1998 using a forecast validation approach which included two or more alternative parallel forecasts. Their results indicate that their models provide acceptable forecasts (better than extrapolative methods) for the explored forecast horizon of one month ahead. Meanwhile we have a number of algorithmic methods to estimate crime hotspot risk (for an overview see Mohler et al. 2015).

Predictive policing can also be tested with field experiment or randomized control trials (hotspot policing experiments) (e.g., Mohler et al 2015, Taylor and Ratcliffe 2020, Ratcliffe et al. 2021). Those studies allow for a more rigorous and controlled evaluation of predictive policing (Fitzpatrick et al. 2019). Applying a large set of field experiments allows consideration of different contextual elements in different environments and locations. It is not always easy to extrapolate from one situation and environment to another. Thus, field experiments only provide partial knowledge as they are localized and specific in focus; reasonable and informed decision making requires mapping of variables with a large number of field experiments. Furthermore, field experiments are often conducted over a short period of time. Taylor and Ratcliffe (2019), for example, suggest running longer experiments and ensuring enough scaling up to achieve statistical power. In general, with an overload and overflow of information, experimental data become even more important. One challenge is to understand what specific activities police officers should be doing in hot spots (Ratcliffe et al. 2021), with the concern being crime displacement. In other words, the proposition is that increased enforcement in one location displaces criminal activities to other locations, although evidence on that does not always hold (Cohen et al. 2007). Nevertheless, terrorist organizations could use crime displacement strategies to distract police forces to incur a stronger negative impact on their targets. Weisburd and Telep (2014) provide a good overview of what is known about hot spot policing. The conclude with a set of questions that allow research to move forward in that area:

> What specific strategies should be used in which specific contexts? While displacement does not threaten the crime control benefits of hot spots policing, are there specific types of displacement that are more likely in specific circumstances? Can we harness legitimacy perceptions in hot spots policing to improve its crime prevention effectiveness, and to lessen negative consequences? Will hot spots policing have long-term as well as the established short-term impacts? Will hot spots policing be effective in smaller cities and rural counties? Will hot spots policing as a generalized policing strategy have overall crime prevention outcomes in a jurisdiction? These are all questions that can now be asked because we already know that hot spots policing is effective (p. 214).

However, the insights on predictive policy are too recent to understand the long-term effectiveness of the method (Hardyns and Rummens 2018). Eagle and Greene (2014) refer to another important aspect, namely the implementation and the importance of respecting citizens when applying such systems:

> An important consideration when developing crime-prediction systems, in particular, is to consider the manner in which those systems are implemented and how they might affect communities that suffer from high crime. It's not new for police to patrol neighborhoods or blocks that could harbor crime, driving or walking routes according to their hunches and conventional wisdom. But it is new to station police at a specific place to wait for trouble. If

executed without proper training and oversight, such system could lead to profiling of types of people, harassment of innocent citizens, and unnecessary arrests (p. 107).

The respect of individual privacy and innocence until proven otherwise is key; police agencies "need to adopt inclusive design and development practices to avoid inadvertent exclusion of communities or hard-coding of (discriminatory) social attitudes into processes" (Kalkanci et al., 2019, p. 2970). Otherwise, they risk public scrutiny and backlash (Murray 2020) and more importantly, may result in damaging outcomes for the society, communities, and people they aim to serve and protect. Essentially, they should take a social-systems approach and "… need to assess the impact of technologies on their social, cultural and political settings" (Crawford and Calo, 2016, p. 311) in which they are both embedded in and contribute towards in order to reach more the sustainable and favorable outcomes offered by AI and related smart technologies for policing and law enforcement. Thus, ethical considerations and aspects around privacy become more important when understanding the use of predictive policing (Hardyns and Rummens 2018). Helbing (2015) advocates that Big Data for criminal investigations should be restricted to activities that endanger a society's function.

Hardyns and Rummens (2018) provide the following policy recommendations: "(1) reliable data collection, (2) clear communication between different police units and hierarchy levels, and (3) police response strategy" (p. 215). As for the police response strategy, they stress that:

> The long-term aim of predictive policing is to establish a decrease in crime rate by promoting a more efficient use of police resources. To realize this, it is important to contemplate the way the risk predictions are handled. At this time, police response strategy and its effect on the (long-term) efficacy of predictive policing is one of the most understudied aspects of the application of predictive policing (p. 215).

4. City Planning and Urban Development

The era of Big Data can also be intimidating, as the proliferation of information technology requires the extraction of order and meaning from what would otherwise be overwhelming noise (Tetlock and Gardner 2015). New technological innovations can address gaps experienced by cities, such as those in their transportation or infrastructure systems. We can identify the digital breadcrumbs or footprints that people leave behind with modern technologies (Pentland 2014, Almaatouq et al. 2016): "Where do people eat, work and play? What routes do they travel? Who do they interact with?" (Pentland 2014, p. 141):

> The important consequence is that the patterns of shared experiences follow the same general rule as the patterns of social ties. The stores, restaurants, and entertainment places that people visit most are also likely to be visited by their friends and so are unlikely to introduce new ideas into their social networks (p. 162).

Using such data allows us to form a better understanding of socio-economic interactions, social activities, and interconnectivity, therefore constituting a better picture of the urban network and its dynamics. Cities still have random encounters, diversity, and variability, which can drive learning and innovation. Cities are organic but evolve faster than biological systems, catalyzed by the continual clash and clang of diverse ideas and dispositions within the subtle backdrop of time and resource scarcity, expanding on centuries of knowledge, learning, and evolution. Cities constantly change over time as they are never finished, always a work in progress (Smith 2019). This also requires thinking about how cities can optimize or improve their structure and dynamics in important areas such as safety, which are closely linked to and dependent on the urban social network. West (2017), for example, discusses this interaction:

> "So any drive toward optimality arising from incremental adaptations and feedback mechanisms as cities grow and evolve hasn't had a lot of time to settle down and reach full fruition" (p. 285).

Planning solutions benefit from considering the power of exploration and engagement and offer the potential for easy face-to-face communication and interaction that allow the flow of information. In the end, cities are a representation of how people interact with one another:

> All socioeconomic activity in cities involves the interaction between people. Employment, wealth creation, innovation and ideas, the spread of infectious diseases, health care, crime, policing, education, entertainment, and indeed, all of the pursuits that characterize modern *Homo sapiens* and are emblematic of urban life are sustained and generated by the continual exchange of information, goods, and money *between* people. The job of the city is to facilitate and enhance this process by providing the appropriate infrastructure such as parks, restaurants, cafés, sports stadiums, cinemas, theater, public squares, plazas, office buildings, and meeting halls to encourage and increase social connectivity (West 2017, p. 316).

But innovations and technological advances require an understanding of how they not only affect efficiency on the engineering side that leverages technology, but also how they benefit citizens and residents of the city. As Green (2019) points out, urban development and design require answering one key question: Whose needs should urban design prioritize (p. 12)? Consensus solutions are required around various trade-offs, such as between personal and social values (Pentland 2014). This requires users to be granted a meaningful voice in developing such priorities and policies and hence, engaging with the decision- making process and reducing the costs to do so. More data in the end also means less privacy (Agrawal et al. 2018) and such trade-offs need to be discussed to achieve procedural fairness and societal cooperation and coordination. For example, when implementing crime-prediction systems it is important and helpful to involve community leaders in the discussion of new technologies and initiatives before they are implemented and rolled out (Eagle and Greene 2014). This means that efficient solutions require thinking and assessing how well the processes and programs meet the needs of its urban residents (Green, 2019, p. 10-11). But technologies themselves offer the possibility to achieve dynamic participatory platforms that engage individuals in a highly democratic way (Helbing 2015, Kennedy and Eberhart 2001).

Sensing data from cities has identified different subgroups of individuals that Pentland (2014) calls tribes: "Members of each tribe choose to go to the same places, eat similar foods, and enjoy the same entertainments" (p. 141). He uses the term behavioral demographics, as those groups show similar preferences and habits. Identifying those behavioral patterns can help in urban planning strategies that allow consideration of the well-being and creative flow of its citizens by considering heterogeneity or by reducing inequality or negative social outcomes. For example, if cities are divided into smaller cities, as found in Beijing due to traffic jams or limited transportation capacities, the rate of idea and informational flows decreases (Pentland 2014). In cities local hubs emerge that behave semi-autonomously even when being hierarchically interconnected (West 2017).

Identifying patterns allows better handling of safety issues, such as societal shocks or socialization disruptions, like those we have seen during COVID-19. Allowing access to mobility data has provided new insights into how human nature interacts and cooperates during a pandemic (see, e.g., Chan et al. 2020a, 20020b, Chan et al. 2020c, Grantz et al. 2020, Pullano et al. 2020, Bickley et al. 2021). Mobility data are important, because if cities facilitate social interactions it is necessary to understand where people are going; people are not generally static most of the time. Mobility is a way of measuring cities' viability and vitality and therefore their health and safety. Big Data provides new opportunities for understanding the dynamics of social interactions by observing actual behavior beyond just beliefs (Pentland 2014, Torgler 2019). Big Data, in general, has changed policy making and the way it affects citizenry (Giest 2017). Real-time data can also help in crisis situations, such as allowing for better evacuation strategies and processes with the use of early warning systems. It allows us to see the direction citizens are driving and allows coordination of traffic across various neighboring counties and states (Eagle and Greene 2014); hence, to track momentary and trending migration to a much higher degree. Sensing data can also identify individual pattern changes and provide early warning signs before a situation becomes dangerous by linking pattern changes to various adverse or undesirable outcomes (Pentland 2014), enabling more *proactive* incident management.

5. Traffic Safety

Cities are dynamic systems that are challenging to understand theoretically and empirically, even in areas that frequently appear in discussions of real-world applications – such as the study of traffic flows in cities. An engineering solution takes into account constraints in space and time of various elements:

> Constraints apply not only to the amount of vehicles on a given road section, but are also generated by conflicts of usage at designated zones (intersections). The combination of the above factors gives rise to highly non-linear and difficult-to-predict dynamics. This explains why traffic can rapidly deteriorate in cities, resulting in widespread congestion and immense societal and environmental costs (Tachet et al. 2016, p. 1-2).

Tachet et al. (2016) provide ways of extending queuing theory, suggesting slot-based interactions which take advantage of advances in intelligent transportation, information, and control systems in traffic management. Vehicles could communicate with roadside infrastructure and other vehicles to improve the coordinate flows and to control the vehicle trajectories more carefully, particularly in case of autonomous driving cars. Slot-based control systems form platoon vehicles, allowing the exploration of efficiency improvements relative to traffic-light-based control that dates back to the end of the 19th century. However, Green (2019) criticizes that:

> [t]here is something missing from the mathematical models and simulations… Their city streets showed no sign of life beyond the flow of cars… Nobody likes traffic, but if eliminating it requires removing people from streets, what kind kinds of cities are we poised to create?" (p. 1).

The use of smart technology could mean vehicles to communicate with pedestrians (e.g., via smart phones) but a coordinated flow may become more challenging to achieve as humans cannot be regulated in the same way as autonomous cars. It also raises the question of how to achieve environmental awareness among humans living in a highly technical environment. The famous Dutch traffic engineer Hans Monderman had an unconventional strategy of reducing traffic signs. Such an approach is in the spirit of Joost Vahl's counter-intuitive traffic engineering, which concluded that you make a traffic junction more dangerous to make it safe (Hamilton-Baillie and Jones 2005, p. 45). Tom Vanderbilt (2008) discusses Monderman in his article *The Traffic Guru*. He recounts him saying that "when you treat people like idiots, they'll behave like idiots" (p. 26). His goal was changing people's behavior by changing the context -- moving away from simple traffic calming strategies such as speed bumps, warnings, signs, bollards, or other highly visible interventions (p. 29). When two children were killed by cars, he was hired as a consultant for the village Oudehaske. He made the environment seem more village like, creating confusion and ambiguity rather than clarity and segregation:

> Signs were removed, curbs torn out, and the asphalt replaced with red paving brick, with two gray "gutters" on either side that were slightly curved but usable by cars. As Monderman noted, the road looked only five meters wide, "but had all the possibilities of six" (p. 30).

Similarly, Tim Harford (2016) in his book *Messy: How to Be Creative and Resilient in a Tidy-Minded World* points out:

> Where once drivers had, figuratively speaking, sped through the village on autopilot – not really attending to what they were doing – now they were faced with a messy situation and had to engage their brains. It was hard to know quite what to do or where to drive – or which space belonged to the cars and which to the village children.

Consequently, drivers became more accommodating as they became unsure which space belonged to whom. Local and temporal contextual knowledge became important and sought after by road users. According to Vanderbilt (2008), Monderman emphasized the importance of the social world where people live and interact: "I don't want traffic behavior, I want social behavior" Monderman stressed (p. 31). However, Moderman also emphasized that removal of such signs and visual markings depends on conditions and context; depending on the context, they are more or less needed. This idea is also often linked to the shared space movement that tries to combine behavioral psychology with changes in perception of risk and safety (Hamilton-Baillie 2008).

AI solutions require careful study of the contextual settings, utilizing the power of observations and attention in the spirit of Allan B. Jacobs (1984):

> You can tell a lot about a city or neighborhood just by looking: something of its history, when it was built, for whom, what physical, social and economic changes have taken place, who lives there now, major issues and problems that may exist, and whether the area is vulnerable to rapid changes (p. 32).

Jacobs' research on boulevard safety shows that applying geometric and physical assumptions or applied logic rather than the observation of real behavior is problematic. Referring to boulevard intersections, he and his co-authors (Jacobs et al. 1994) explained:

> The sheer numbers of possible conflicting movements – weaves from side access roads to the central lanes and, vice versa, possible right turns from central lanes across straight moving traffic on the access roads, to name two example – suggest logically that boulevards must not be as safe as other streets. Our research suggests otherwise (p. 7).

Thus, boulevards seem to function better that expected while performing their multi-purpose functions. Looking at Barcelona, they also pointed out:

> The main point of the argument against boulevards is that the complexity of movements in intersections makes them unsafe. And yet in Barcelona, this has been largely resolved by a pattern of traffic organization which relies on alternating one-way streets. The intersections along the Paseo de Gràcia are thus greatly simplified, and the number of conflict points reduced. Consequently one would have expected, in Barcelona, less of a difference between the safety record of boulevards arid control streets. However, it seems that the simplification of the intersections has not improved the safety of boulevards, but perhaps made it worse (p. 87).

Jacobs suggested that contrary to traditional planning assumption, the segregation of cars and pedestrians decreases safety and community vitality by making cars more aware that they are integrated in the pedestrian realm (Hamilton-Baillie, 2008, p. 162). Hamilton-Baillie and Jones (2005) discuss experiments applied in Europe that removed standard curbs, barriers, signs, and road markings. This forced motorists to use more eye contact with other road users and pedestrians. The experiment showed increased safety for cyclists and pedestrians and contributed to making the urban environment more attractive. Helbing (2015) stresses insights for a study that indicates a bottom-up self-regulated approach in traffic control performed better than a centralized top-down regulated approach. In general, smart cities could think and engage more into the possibilities of creating self-regulating systems. Helbing stresses that guided self-organization provides a fruitful and promising way of managing complex dynamic systems:

> The underlying idea is to exploit, rather than fight, the inherent tendency of complex systems to self-organize and thereby create a robust, ordered state. For this, it is important to have the

right kinds of interactions, adaptive feedback mechanisms, and institutional settings, i.e., to establish proper 'rules of the game' (p. 72).

6. Public Health

Public health aims to improve the health of the population, so it focuses on community outcomes, interventions, and behavior change, and tends towards prevention rather than treatment – a last resort. Public health is concerned with the whole gamut of human health including physical, mental, and social wellbeing, and is a core element of any successful and safe city. The difficulty in public health lies in the 'wicked' and multi-faceted problems it faces and the complex interactions and interdependencies between both the actors and institutions responsible for delivery public health initiatives and the end users (the public) who engage with their advice, services, and treatment. All this forms a very complex environment wherein mistakes are bound to happen from time to time, but these mistakes come with high stakes – sometimes a human life is on the line. It is for this reason that AI in public health is both exciting and daunting; the stakes are high and the rewards sometimes higher in such "a complex network of individuals and organizations … creating the conditions for [public] health" (IOM, 2002, p. 28). Public health interventions themselves are then complex systems (Hawe 2015) – again, an area where AI methods and other smart technologies can contribute and succeed.

Government is often expected to fulfil the primary role in coordinating and delivering public health (see for example, IOM's (2002) 'The Ten Essential Public Health Services') and these efforts are generally focused on three broad levels (Schneider, 2020): *primary* (preventing exposure to risk factors), *secondary* (minimizing severity/damage), and *tertiary* (minimizing disability). For example, AI has been applied at the primary level through more targeted public health promotion leveraging social networking sites (Capurro et al. 2014, Welch et al. 2016), the secondary level by advanced forms of AI screening for early detection of cancers (Hu et al. 2019), and the tertiary level by greatly increasing the detection performance in radiology (Hosny et al. 2018) hence, ensuring the targeted and effective treatment of malign cells and medical conditions unobservable to the human eye alone. The inherent sensitivity of public health to political influence requires that we have transparent tools and methods (O'Malley et al. 2009) and communication of such, a challenge for the typical 'black box' implementation of AI in current times. The transparency of a system is a particularly important determinant of human-machine trust development (Chen and Barnes 2014). Trust in turn is a strong predictor of how systems may be used / mis-used (Chen and Barnes 2014, de Visser et al. 2018) and hence, determines the sustainability of AI applications in 'real world' settings and situations. Other human-related factors of human-machine trust development include propensity to trust (Stowers et al. 2017), task loading (Chen and Barnes 2014), expertise, personal characteristics (e.g., age, gender, personality), and sociocultural factors (Schaefer 2016).

Given its strengths in natural language processing, AI could be used to enable an automated and more proactive incident management when combined with incident reporting tools and a structured framework of incident causation in public health, such as HFACS-PH (Bickley and Torgler 2021). Machine learning methods have already been used to analyze, classify, and even predict safety incidents from 'raw' text in incident reports (Kurian et al. 2020, Madeira et al. 2021) and in engineering risk assessments more generally (Hegde and Rokseth 2020). This can also apply more broadly to proactive incident management in other high-risk, high-reliability domains such as mining, oil & gas, maritime, aviation, and space exploration. Here we expect, "[m]achine learning provides a powerful tool to hear, more clearly than ever, what the data have to say" (Mullainathan and Spiess, 2017, p.104); in this case, we are listening to what the data have to say about incidents and the prevention of same.

7. Use, Application, and Implementation of Smart Technologies

When applying those insights to the developed smart and livable city, it is important to understand how one needs to plan for technical innovations and development of new demands on the city – such as self-driving cars, and an interactive transport system. How do self-driving cars and other automated technologies fit in to tight and loose bonds and the importance of incidental, spontaneous interactions? The question of how to make a city more equitable, sustainable, and economically and socially responsible suggests positive and negative aspects in safety that require careful discussion. Another important question for further exploration: how much structure or messiness is ideal? Automation can produce substantial problems if humans become less skilled in coping with atypical conditions. Harford (2016) discusses negative externalities of automation in aviation, referring also to Earl Wiener's Laws of aviation and human error. For example, "[d]igital devices tune out small errors while creating opportunities for large errors" (Harford, 2016, p. 199). Understanding how large errors arise is particularly important when implementing AI solutions. Common sense reasoning and training can act as an additional safeguard when technologies are not working properly. Although GPS systems are very reliable, there have been enough cases where people drove their cars into seas, lakes, or houses based on instructions provided by their GPS (Harford, 2016, p. 206-207). As Harford (2016) points out,

> [w]hen the algorithms are making the decisions, people often stop working to get better. The algorithms can make it hard to diagnose reasons for failures. As people become more dependent on algorithms, their judgement may erode, making them depend even more on the algorithms. That process sets up a vicious cycle. People get passive and less vigilant when algorithms make the decisions (p. 208).

This suggests that a careful discussion should occur on how one needs to combine aspects such as adaptability, flexibility, judgement, tacit knowledge, and competence with the reliability and acceptability of AI to reduce and cope with accidents and increase safety. AI systems themselves can help in creating more sophisticated and realistic scenarios of options that cities may pursue, which speeds up the entire process (an important element when considering sustainability aspects). More information may also help in increasing the willingness to experiment with new potential solutions. Successful experiments can then be implemented in other environments and cities, encouraging creativity and innovation via learning from successes and failures. Interventions can target specific environments within cities such as neighborhoods who suffer inequality, unemployment, lack of access to public facilities and infrastructure, lack of healthcare, etc. This also allows one to go into the micro-structure of human behavior but requires a good understanding of individual preferences and incentives. Pentland (2014) has criticized that current city system designs rely too much on financial incentives, stressing that:

> unfortunately, experience shows that this approach rarely works very well, especially in tragedy of the commons situations. Moreover, using financial incentives privileges the rich. As an example, consider congestion pricing as a method of managing traffic. By charging people more to drive in certain places, we allow rich people to go where they want and keep out the poor. This is particularly worrisome because exploration results in innovation, so by reducing the amount of exploration that the poor can achieve, we are also reducing their community's capacity for development and social improvement (p. 15).

For example, a lack of good public transportation systems can lead to individuals missing or being late to appointments (e.g., doctor appointments), which affects their health and well-being. Low-income environments are also affected by the ability to use smart apps, which are often linked to bank account access or credit card information (Green 2019). In addition, wealth allows investment in more exploration (Pentland 2014) and therefore the ability to take better advantage of the opportunities offered by a city. In addition, different age demographics have different capabilities of using new technologies. App mentality or app-dependencies have their own problems. Gardner and Davis (2013) have emphasized some issues around that with a particular focus on young people. An app mentality affects how we perform discrete tasks such a locating a restaurant. It promotes an algorithmic way of thinking and allows little room for ambiguity or uncertainty before arriving to a solution, decision, or destination: "[t]hey've come to think of the world as an ensemble of apps, to see their lives as a string of ordered apps, or perhaps, in many cases, a single, extended, cradle-to-grave app" (p. 7). Thus, technology can recreate and change human psychology and can therefore have transformative effects on how we think and act. According to Gardner and Davis (2013), this may lead to an increase in risk aversion in the way young people approach and express their schoolwork, friendship, personal expression, personal identity and intimacy, imagination, or their creative pursuits:

> Information apps take away the risk of giving an incorrect answer, whereas location apps eliminate the risk of getting lost in an unfamiliar place. It strikes Katie and Howard as a remarkable fact that Molly [Katie's sister] has never had the experience of being lost. Each of us can recall instances from our youth when we didn't know where we were and didn't have immediate access to a parent to guide us to familiar territory. Though scary, these experiences stand out in our memories because they tested our resiliency and gave us a sense of autonomy. Such experiences are foreign to Molly. With her map app and ability to call her parents at any time, she can always be sure of where she is and how to get to her next location . . . unless she loses her cell phone! (p. 84).

Technology is also able to help with socio-demographic challenges we are facing. Longitudinal planning in smart cities takes into account that more people are reaching longer life spans. Cities therefore need to proactively address such needs of the elderly population; this may be done via simple actions such as removing physical steps, or by finding ways of increasing visibility and security such as lighting up streets better (Smith 2019).

In general, deploying smart technology requires an understanding of the challenges faced by cities when thinking about policy solutions that improve peoples' lives. A sensing city depends on systems that people use, requires compatibility with human nature (Pentland 2014), and with social and economic conditions of its citizens. Green (2019) suggests applying "a research process that focuses on people rather technology" (p. 34). The challenge is to still build a human-centered city when integrating new technologies and data points (Pentland 2014).

Green stresses the danger of applying tech goggles; explaining that technology presents neutral and optimal solutions to social problems. These solutions are the primary mechanism of social change, therefore neglecting the barriers between social and political dynamics. The history of technological innovation is full of such examples, as nicely shown by Juma (2016). Societies are constantly subject to the tension between the need to innovate and the pressure to maintain continuity, social order, or stability. For example, new technologies encounter more enemies if they are more likely to challenge our existing habits. Innovations are challenged by their perceived risk in terms of physical, social, and economic consequences as people tend to avoid risks. Juma (2016) stresses that "debates over new technologies are framed in the context of risks to moral values, human health, and environmental safety. For example, safety concerns are often used as a reason to express issues or push back or fight against new technologies. But behind these genuine concerns often lie deeper, but unacknowledged, socioeconomic considerations" (p. 6). Thus, changes in technology require changes in social institutions, and Juma stresses that existing institutions may not be well enough equipped to address emerging technologies or may require long periods of adjustments to accommodate the needs of new technologies (p. 199). Boulding (1964) also stresses that

> [c]hanges in technology produce change in social institutions, and changes in institutions produce change in technology. In the enormously complex world of social interrelations we cannot say in any simple way that one change produces the other, only that they are enormously interrelated and both aspects of human life change together (p. 9).

Advancement in technologies often help to address concerns regarding technological innovations:

> safety concerns regarding early mechanical refrigeration could not be addressed without advances in technology. Similarly, the rapid rate at which early tractors were improved helped to foster their adoption. Recent concerns about obtaining stem cells from human embryos have been addressed by innovative approaches that helped to identify other sources (Juma 2016, p. 15).

Juma (2016) also stresses that lessons learned from controversies over agricultural or pharmaceutical technologies may help in developing strategies for emerging technologies such as AI, robotics, or drones. Public perceptions of early tractors were unfavorable. They were seen as less reliable than horses.

> Businesses, however, did not consider the tractor to be a good investment. The tractor did not operate as smoothly as the horse; maintenance often cost more than the purchase price; and its

> size and weight made it impractical for the small farm… Some of the final obstacles to tractor use were broken down once the machine became more reliable and versatile, but company malfeasance threatened to erode consumer trust irrevocably… There were genuine concerns that the adoption of the tractor would render farmers dependent on urban supplies of expertise, spare parts, fuel, and other inputs that were previously available on the farm. Horses could reproduce themselves, whereas tractors depreciated. This became a potent argument against the technology (p. 125-129)

However, technological improvements and a steep but rewarding learning curve helped a lot as engineers could upgrade tractors faster than breeders could improve horse performance. Similarly, smart city engineers and designers could upgrade innovations, flows, processes, and interactions faster than politicians can currently legislate to change policy, targeting behaviors or establishing new social institutions. This may be a good or bad thing, and will depend on the engineers or the original developers of the AI that acts as the smart city engineers. Existing norms and images filter or censor information which best support the current structures (Boulding 1965).

Smart city innovations occur on the ground, and the ground provides safety concerns that need to be evaluated or integrated. As a city is a dynamic system, data needs to be collected and merged from various sources. Jacobs' approach is interesting because it helps to look at reality without theoretical preconceptions of any kind. Observing means proximity to the problem. It allows learning from both experimentation and doing. It allows generation of what Clifford Geertz (1974) would term "experience-near" knowledge. Observing an environment provides cues for prerequisites of advancements. Including and conversing with all decision-makers, actors, and stakeholders provides more insights into spotting possibilities and problem-solving strategies for everyday challenges and opportunities. A bottom-up approach provides a better micro-foundation for the problems involved. Local knowledge is part of the scientific solution problem. The universal desire for power may lead to the optical illusion that a blueprint for technological adaptation can be designed from the top down. The propensity to play requires the complementary value of propensity to experiment and improvise. Experimentation also assumes that failures happen; yet, learning from failure is an important strategy for success. Designing better cities requires an understanding of fine-grained social interactions and ties (Pentland 2014). As West (2017) stresses,

[t]he city is not a top-down engineered machine dominated by straight lines and classic Euclidean geometry, but rather is much more akin to an organism with its crinkly lines and fractal-like shapes typical of a complex adaptive system – which it is (p. 290).

Looking at the fractal dimension then allows to understand the health and robustness of cities.

8. Conclusions

Cities are historically robust entities. Many successful ancient cities are still here: "Athens, Rome, London, Kyoto, Delhi, Baghdad, Cairo, Mexico City, Lyons, Carthage, Marseille, Quito, Xi'an, Jakarta, Istanbul, Samarkand, Cuzco" (Smith 2019, p. 253). Cities are a good test group for exploring how Big Data can help in better understanding the dynamics of such a system.

The resulting positive feedback loops act as drivers of continuous multiplicative innovation and wealth creation, leading to superlinearscaling and increasing returns to scale. Universal scaling is a manifestation of an essential trait resulting from our evolutionary history as social animals common to all people worldwide, transcending geography, history, and culture. It arises from the integration of the structure and dynamics of social networks with the physical infrastructural networks that are the platform upon which the panoply of urban life is played out. Although this is a dynamic beyond biology, it shares a similar conceptual framework and mathematical structure es exemplified by fractal-like network geometries" (West 2017, p. 284).

Urban science allows combining the knowledge not just of engineers and architects but also anthropologists, sociologists, historians, economics, or scholars in the area of computer science. AI and Big Data provide new ways to think about aspects such as sustainability, safety, connectivity, attractiveness, and desirability with a dynamic perspective. As Smith (2019, p. 244) points out, the infrastructure of cities has the "inherent capacity for framing social interactions and for contributing to social justice" (p. 244). Scholars have started to think more about how social infrastructure can deal with the negative factors such as inequality, polarization or the decline of civic life as physical conditions determine whether social capital develops (Klineberg 2016). The ability to identify, protect and nurture social capital is an important task for a smart city.

Safety is an important hallmark of a successful city and it contributes the ability enjoy ambience, culture and social interactivity and connectivity, and supports a sense of community and commitment. In this paper we have tried to show that AI and Big Data solutions require taking into account the human component to successfully design smart, livable, and flourishing city.

References

Abu-Rayash, A., & Dincer, I. (2020). Analysis of the electricity demand trends amidst the COVID-19 coronavirus pandemic. *Energy Research & Social Science*, 68, 101682.

Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction machines: the simple economics of artificial intelligence*. Harvard Business Press.

Alexandrie, G. (2017). Surveillance cameras and crime: a review of randomized and natural experiments. *Journal of Scandinavian Studies in Criminology and Crime Prevention*, 18(2), 210-222.

Baker, A. L., & Keebler, J. R. (2017). Factors affecting performance of human-automation teams. In Advances in Human Factors in Robots and Unmanned Systems (p. 331-340). Springer.

Bickley, S. J., Chan, H. F., Skali, A., Stadelmann, D., & Torgler, B. (2020). How Does Globalisation Affect COVID-19 Responses, forthcoming in: *Globalization and Health*.

Bickley, S. J., Macintyre, A., & Torgler, B. (2021). Artificial Intelligence and Big Data in Sustainable Entrepreneurship (No. 2021-11). Center for Research in Economics, Management and the Arts (CREMA).

Bickley, S.J., & Torgler, B. (2021). A Systematic Approach to Public Health – Novel Application of the Human Factors Analysis and Classification System to Public Health and COVID-19, forthcoming in: *Safety Science*.

Boulding, K. E. (1964). *The Meaning of the 20th Century: The Great Transition*. Harper Colophon Books.

Capurro, D., Cole, K., Echavarría, M. I., Joe, J., Neogi, T., & Turner, A. M. (2014). The use of social networking sites for public health practice and research: a systematic review. *Journal of Medical Internet Research*, 16(3), e79.

Chan, H. F., Skali, A., Savage, D. A., Stadelmann, D., & Torgler, B. (2020a). Risk attitudes and human mobility during the COVID-19 pandemic. *Scientific Reports*, 10(1), 1-13.

Chan, H. F., Brumpton, M., Macintyre, A., Arapoc, J., Savage, D. A., Skali, A., Stadelmann, D. & Torgler, B. (2020b). How confidence in health care systems affects mobility and compliance during the COVID-19 pandemic. *PloS One*, 15(10), e0240644.

Chan, H. F., Moon, J. W., Savage, D. A., Skali, A., Torgler, B., & Whyte, S. (2020c). Can psychological traits explain mobility behavior during the COVID-19 pandemic?. *Social Psychological and Personality Science*, 1948550620952572.

Chen, J. Y., & Barnes, M. J. (2014). Human–agent teaming for multirobot control: A review of human factors issues. *IEEE Transactions on Human-Machine Systems*, 44(1), 13-29.

Chiou, E. K., & Lee, J. D. (2016). Cooperation in human-agent systems to support resilience: A microworld experiment. *Human factors*, 58(6), 846-863.

Cohen, J., Gorr, W. L., & Olligschlaeger, A. M. (2007). Leading indicators and spatial interactions: A crime-forecasting model for proactive police deployment. *Geographical Analysis*, *39*(1), 105-127.

Crawford, K., & Calo, R. (2016). There is a blind spot in AI research. *Nature News*, 538(7625), 311.

de Visser, E. J., Pak, R., & Shaw, T. H. (2018). From ‘automation’to ‘autonomy’: the importance of trust repair in human–machine interaction. *Ergonomics*, 61(10), 1409-1427.

Eagle, N., & Greene, K. (2014). *Reality mining: Using big data to engineer a better world*. MIT Press.

Fitzpatrick, D. J., Gorr, W. L., & Neill, D. B. (2019). Keeping score: Predictive analytics in policing. *Annual Review of Criminology*, 2, 473–491.

Gardner, H., & Davis, K. (2013). *The app generation: How today's youth navigate identity, intimacy, and imagination in a digital world*. Yale University Press.

Geertz, C. (1974). " From the native's point of view": On the nature of anthropological understanding. *Bulletin of the American Academy of Arts and Sciences*, 28(1), 26-45.

Giest, S. (2017). Big data for policymaking: fad or fast track? *Policy Sciences*, 50(3), 367-382.

Grantz, K.H., Meredith, H.R., Cummings, D.A., Metcalf, C.J.E. (2020). The use of mobile phone data to inform analysis of COVID-19 pandemic epidemiology. *Nature Communications*. 11(1):4961.

Green, B. (2019). *The smart enough city: putting technology in its place to reclaim our urban future*. MIT Press.

Hamilton-Baillie, B. (2008). Shared space: Reconciling people, places and traffic. *Built Environment*, *34*(2), 161-181.

Hamilton-Baillie, B., & Jones, P. (2005, May). Improving traffic behaviour and safety through urban design. In *Proceedings of the Institution of Civil Engineers-Civil Engineering* (Vol. 158, No. 5, p. 39-47). Thomas Telford Ltd.

Hardyns, W., & Rummens, A. (2018). Predictive policing as a new tool for law enforcement? Recent developments and challenges. *European Journal on Criminal Policy and Research*, 24(3), 201-218.

Harford, T. (2016). *Messy: How to be creative and resilient in a tidy-minded world*. Hachette UK.

Hawe, P., 2015. Lessons from complex interventions to improve health. Annual review of public health, 36, 307-323.

Hegde, J., & Rokseth, B. (2020). Applications of machine learning methods for engineering risk assessment–A review. *Safety science*, 122, 104492.

Helbing, D. (2015). *Thinking ahead-essays on big data, digital revolution, and participatory market society*. Springer.

Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. J. (2018). Artificial intelligence in radiology. *Nature Reviews Cancer*, 18(8), 500-510.

Hu, L., Bell, D., Antani, S., Xue, Z., Yu, K., Horning, M. P., ... & Schiffman, M. (2019). An observational study of deep learning and automated evaluation of cervical images for cancer screening. JNCI: *Journal of the National Cancer Institute*, 111(9), 923-932.

Jacobs, A. B. (1984). Looking at Cities. *Places*, 1(4), 28-37.

Jacobs, A. B., Rofé, Y. Y., & Macdonald, E. S. (1994). Boulevards: A Study of Safety, Behavior, and Usefulness. UCTC Working Paper N. 248, University of Berkeley.

Juma, C. (2016). *Innovation and its enemies: Why people resist new technologies*. Oxford University Press.

Kalkanci, B., Rahmani, M., & Toktay, L. B. (2019). The role of inclusive innovation in promoting social sustainability. *Production and Operations Management*, 28(12), 2960-2982.

Kennedy, J., & Eberhart, R. C. (2001). *Swarm Intelligence*. Morgan Kaufmann Publishers.

Kerstholt, J., Barnhoorn, J., Hueting, T., & Schuilenborg, L. (2019). Automation as an Intelligent Teammate: Social Psychological Implications. In *NATO-HAT Symposium on Human Autonomy Teaming*.

Klinenberg, E. (2018). *Palaces for the people: How to build a more equal and united society*. Random House.

Kurian, D., Sattari, F., Lefsrud, L., & Ma, Y. (2020). Using machine learning and keyword analysis to analyze incidents and reduce risk in oil sands operations. *Safety Science*, 130, 104873.

Madeira, T., Melício, R., Valério, D., Santos, L., 2021. Machine Learning and Natural Language Processing for Prediction of Human Factors in Aviation Incident Reports. *Aerospace*, 8(2), 47.

Metcalf, L., Askay, D. A., & Rosenberg, L. B. (2019). Keeping humans in the loop: pooling knowledge through artificial swarm intelligence to improve business decision making. *California Management Review*, 61(4), 84-109.

Mohler, G. O., Short, M. B., Malinowski, S., Johnson, M., Tita, G. E., Bertozzi, A. L., & Brantingham, P. J. (2015). Randomized controlled field trials of predictive policing. *Journal of the American Statistical Association*, *110*(512), 1399-1411.

Mullainathan, S., & Spiess, J. (2017). Machine learning: an applied econometric approach. *Journal of Economic Perspectives*, 31(2), 87-106.

Murray, D. (2020). Using Human Rights Law to Inform States' Decisions to Deploy AI. *AJIL Unbound*, 114, 158-162.

O'Malley, P., Rainford, J., & Thompson, A. (2009). Transparency during public health emergencies: from rhetoric to reality. *Bulletin of the World Health Organization*, 87, 614-618.

Ostrom, E. (2000). Collective Action and the Evolution of Social Norms. *The Journal of Economic Perspectives*, 14: 137-158.

Pentland, A. (2014). *Social physics: How good ideas spread-the lessons from a new science*. Penguin.

Pullano, G., Valdano, E., Scarpa, N., Rubrichi, S., Colizza, V. (2020). Evaluating the effect of demographic factors, socioeconomic factors, and risk aversion on mobility during the COVID-19 epidemic in France under lockdown: a population based study. *The Lancet Digital Health*. 2(12): E638-E649.

Ratcliffe, J. H., Taylor, R. B., Askey, A. P., Thomas, K., Grasso, J., Bethel, K. J., ... & Koehnlein, J. (2020). The Philadelphia predictive policing experiment. *Journal of Experimental Criminology*, 1-27.

Sabattini, L., Villani, V., Fantuzzi, C., Czerniak, J. N., Mertens, A., Loch, F., & Vogel Heuser, B. (2018). Methodological Approach for the Evaluation of an Adaptive and Assistive Human-Machine System. *2018 IEEE 14th International Conference on Automation Science and Engineering* (CASE).

Schneider, M., 2020. *Introduction to public health*. Jones & Bartlett Learning, Burlington, US.

Smith, M. L. (2019). *Cities: The First 6,000 Years*. Penguin Books.

Stowers, K., Oglesby, J., Sonesh, S., Leyva, K., Iwig, C., & Salas, E. (2017). A Framework to Guide the Assessment of Human–Machine Systems. Human Factors: *The Journal of Human Factors and Ergonomics Society*, 59(2), 172-188. https://doi.org/10.1177/0018720817695077

Tetlock, P. E., & Gardner, D. (2016). *Superforecasting: The art and science of prediction*. Random House.

Tachet, R., Santi, P., Sobolevsky, S., Reyes-Castro, L. I., Frazzoli, E., Helbing, D., & Ratti, C. (2016). Revisiting street intersections using slot-based systems. *PloS one*, *11*(3), e0149607.

Taylor, R. B., & Ratcliffe, J. H. (2020). Was the pope to blame? Statistical powerlessness and the predictive policing of micro-scale randomized control trials. *Criminology & Public Policy*, 19(3), 965-996.

Torgler, B. (2019). Opportunities and challenges of portable biological, social, and behavioral sensing systems for the social sciences. In Gigi Foster (Ed.), Biophysical measurement in experimental social science research (p. 197-224). Academic Press.

Torgler, B., García-Valiñas, M. A., & Macintyre, A. (2010). *Participation in environmental organizations*. Routledge.

US Institute of Medicine (IOM), 2002. *The Future of the Public's Health in the 21st Century National Academies Press*, Washington, US. PMID: 25057638.

Vanderbilt, T. (2008). The traffic guru. *The Wilson Quarterly (1976-)*, *32*(3), 26-32.

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M., & Nerini, F. F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. *Nature communications*, 11(1), 1-10.

Weisburd, D., & Telep, C. W. (2014). Hot spots policing: What we know and what we need to know. *Journal of Contemporary Criminal Justice*, 30(2), 200-220.

Welch, V., Petkovic, J., Pardo, J. P., Rader, T., & Tugwell, P. (2016). Interactive social media interventions to promote health equity: an overview of reviews. *Health promotion and chronic disease prevention in Canada: research, policy and practice*, 36(4), 63.

West, G. (2017). *Scale: The Universal Laws of Growth, Innovation, Sustainability, and the Pace of Life in Organisms, Cities, Economies, and Companies*. Penguin Press.