PULTE INSTITUTE
FOR GLOBAL DEVELOPMENT

Policy Guidelines for Smart Sanitation Technology as a Public Health Tool

Carnovale, Maria

UNIVERSITY OF NOTRE DAME | KEOUGH SCHOOL OF GLOBAL AFFAIRS

Policy Guidelines for Smart Sanitation Technology as a Public Health Tool

Carnovale, Maria

Report prepared for the Pulte Institute for Global Development,
part of the Keough School of Global Affairs, University of Notre Dame

3150 Jenkins Nanovic Halls
Notre Dame, Indiana 46556
(574) 631-2940
Website: pulte.nd.edu
Email: globaldevelopment@nd.edu

TABLE OF CONTENTS

ABOUT THE AUTHORS

Maria Carnovale is a Senior Policy Advisor at Katametron, Lecturer at the Johns Hopkins School of Advanced International Studies (SAIS), and a freelance writer. She studies the conditions that are necessary for technology to maximize well-being without damaging individuals and communities, and what policies can foster this process.

An economist by training, after receiving her PhD in Public Policy from Duke University in 2019, she joined SAIS as a postdoctoral fellow. In 2020, she was a Lead Policy Analyst at the Duke Initiative for Science and Society, before joining the Harvard Kennedy School as Technology and Human Rights Fellow from 2020 to 2022. In 2021, she served as Vice President at the Institute for Technology and Global Health where she led the communications team.

*The views expressed in this publication do not necessarily reflect the views of Chemonics International, Inc.

ABSTRACT

Smart sanitation technology, or SST, refers to digital technologies applied to the sanitation industry. The breadth of applications can be wide, but they are quickly rising as popular public health tools, especially thanks to their potential for epidemiological analysis. While SST might sustain the vision of the UN Sustainable Development Goals, it can also lead the continuous surveillance of individual existence—an often-criticized feature of smart city architecture—to an exceedingly private location: the toilet. The data collected by many SST applications can be considered health data, the improper use of which can generate harm and stigma. This paper provides the first discussion of a policy framework for this technology by applying basic and uncontroversial principles (scientific evidence, necessity, proportionality, time boundedness, and privacy) to the use of SST for public health purposes.

INTRODUCTION

Sanitation infrastructure delivers many essential services, including access to sanitation installations, management of wastewater, and prevention of water pollution. Increasingly, the digital revolution has had a major impact on the sanitation sector. It has allowed the automated collection of data to monitor the functioning and performance of the infrastructure, citizens' use of its installations, and the presence of pathogens in the wastewater (Toilet Board Coalition 2021). The term Smart Sanitation Technology (SST) has come to identify these and other applications of digital technology to the sanitation industry.

SSTs are still emerging, but they are quickly rising as critical public health tools, especially in response to the COVID-19 pandemic. There are already multiple use cases: The UK set up a sewage monitoring system to collect COVID-19 data in the local wastewater (Gill 2021); the city of Cambridge, MA employed a similar system with the support of Biobots Analytics-- an MIT spin-off that offers computational tools to analyze wastewater data (City of Cambridge MA 2020).

Epidemiological analysis of the sewage system, however, has a long history that precedes the COVID-19 pandemic. Many of its applications have monitored the transmission of other diseases such as noroviruses (Muscillo et al. 2013; Sharif et al. 2020), polio (Goodridge 2020; Hovi et al. 2001; Riordan 1962), hepatitis A (Hellmér et al. 2014), and antibiotic resistance (Dai et al. 2019; Sharif et al. 2020).

Digitalization quickly became part of these processes. For instance, in 2018, the city of Pune, India, included wastewater monitoring in its smart city data collection and visualization system to improve the provision of sanitation services, increase the efficiency of wastewater treatment and management, and improve the prevention of common ailments such as diarrhea, typhoid, dysentery, diabetes, and hypertension (Toilet Board Coalition 2018). Other uses of SST include the collection of data to monitor the status and use of sanitation infrastructure (GSMA 2017; Morais and Kore 2020) and automatize its maintenance (Garv n.d.), or monitor individual health trends (Coprata n.d.; Park et al. 2020).

It is in impoverished communities—where inadequate infrastructure for water, sanitation, and hygiene (WASH) causes a higher prevalence of water-borne illnesses—that SSTs have been most welcomed. Lack of improved sanitation is a major contributing factor to under-five childhood mortality in developing countries, mostly through diarrhea and other water-related illnesses (Tumwine et al. 2002). Globally, 3.3% of deaths and 4.6% of disability-adjusted life years are attributed to diseases connected to poor water sanitation and hygiene (WASH), over half of them in Sub-Saharan Africa alone (WHO 2019). In 2019, countries that rank low on the Sustainable Development Index had 8.62% of deaths caused by diarrheal disease (IHME n.d.). Between 2012 and 2015, healthcare costs and loss in economic productivity from poor sanitation caused a financial burden of an estimated $260 billion worldwide (Hutton 2013).

The World Health Organization has published a set of guidelines to monitor the health of communities worldwide using a variety of water-borne disease indicators (World Health Organization and United Nations Economic Commission for Europe 2019), and address outbreaks. SSTs might provide an avenue to expedite this process (Impouma et al. 2020) and lower its cost by better targeting public health interventions. The underdevelopment of the sanitation infrastructure in many low-income countries offers the opportunity to leap-frog to solutions with a digital component (UNICEF 2021). In high-income countries with a higher prevalence of non-communicable diseases (IHME n.d.) like diabetes or cancer, SSTs might help fill gaps in preventive care (Borsky et al. 2015).

Nevertheless, these technologies present important ethical concerns. The machine learning systems that often power SSTs can find correlations in large datasets, but often cannot pinpoint causation, with the risk of generating inaccurate conclusions (Blyth 1972; Boyd and Crawford 2012; Valiant 1984). Machine learning algorithms adapt to the dataset they operate on and can often become opaque to their users—it is hard to understand what drives their outputs-- hampering the recognition of any estimation bias (de Laat 2017; Mittelstadt et al. 2016). When flawed inference misinforms policy intervention, it can lead to the misidentification of issues (Danks and John London 2017; Shah 2018), unnecessary health surveillance, and stigma (Kitchin 2014, 2016). The sensitive nature of health data raises concerns over its collection, use, and sharing. Therefore, to be a driver of sustainable development, SSTs must comply with privacy and ethical standards.

This paper provides an overview of the state of the art of SST, forecasted trends, and use cases. It also makes policy recommendations based on ethical and human rights considerations that should guide all on-the-ground implementation of SSTs. To our knowledge, this paper provides the first analysis of the issue and proposed solutions.

What is Smart Sanitation?

The breadth of SST applications can be wide. Monitoring systems that support municipalities as they manage their sanitation infrastructure, mobile applications that match sanitation services to users, biosensors used for epidemiological monitoring, and sensors to support individual health management are widely different systems that fall under the umbrella of smart sanitation. In the next section, some broad applications of SST are reviewed.

SST for Infrastructure Management

In its most general form, SST is part of the broader Smart City trend which employs digital technologies, the collection, and the analysis of data from around the city to streamline the management of public services and provide information for further planning. Under this framework, municipalities might work to map and track their wastewater systems, check the health of their infrastructure, and perform regular maintenance.

In 2020, the Kampala Capital City Authority (KCCA) developed a GIS-based platform to map pit latrines and septic tanks in the city of Kampala, Uganda. In Kampala, 70% of the population relies on pit latrines, and 94% of the population does not have access to sanitation directly connected to a formal sewage system (Morais and Kore 2020). Platform users are able to upload information about a septic tank or pit latrine, including its location. The system matches them to the closest registered pit emptier, thus facilitating the collection of waste. It also collects data on the characteristics of the sanitation facility and the transaction, such as the amount paid or the volume emptied. Of the 85% of pit emptiers who use the app, 63% reported an increase in their income, suggesting that the app improved the connection between sanitation service providers and their market. It allowed authorities to collect data that might guide the allocation of resources and the future development of the city's sanitation infrastructure (Knezovich and Vairavamoorthy 2021; Morais and Kore 2020).

SST can also collect data on the use and maintenance of sanitation facilities. The India-based company, GARV, developed self-cleaning toilet stalls that can be installed in public spaces (Garv n.d.). On top of automatically cleaning themselves, the stalls collect data on the number of people who visited the toilet, how many of the visitors flushed or used the soap dispenser, and the amount of water used (Toilet Board Commission 2021). The data collected might inform targeted public health interventions like educating communities on hygiene practices and stewardship of natural resources. The city of Pune, India, among others, has adopted these systems.

Both applications, KCCA's GIS-based map and GARV's public restrooms, show encouraging results: the solutions seem to be well perceived by their users (Toilet Board Commission 2021) while providing information to local policymakers . Nevertheless, there needs to be further assessment of whether these systems achieve their ultimate objective: improving health outcomes in the adopting communities.

SST for Epidemiological Monitoring

SST also includes the use of sensors in toilets, sewage pipes, and septic tanks that collect data to infer the health status of the community of reference by studying its wastewater. Data collection is performed by a variety of systems including biosensors, acoustic, and visual sensors. Acoustic and visual sensors record sound and images respectively which are then used as inputs in algorithms that predict the probability of diseases (Costa 2020; Ghayvat, Pandya, and Patel 2020; Song et al. 2014). A biosensor is a device that generates a signal whenever it detects a target of analysis. For instance, a glucose biosensor can detect the presence of glucose in a person's blood, quantify it, and communicate it to the user, either directly, or by sending the data from the biosensor to a mobile application (Kim et al. 2019). Biosensors applied in sanitation contexts can detect biomarkers present in wastewater (Rary et al. 2020). They have been used to track the presence or diffusion of infectious diseases, such as HIV (De La Rica and Stevens 2012), E.coli, and tuberculosis (Yang et al. 2015), cancer markers (Lucarelli et al. 2002; Maraldo, Garcia, and Mutharasan 2007) and other pathogenic bacteria (Webster et al. 2014). A study used the mix of bacteria found in the sewage system to predict the prevalence of obesity in the population of reference (Newton et al. 2015). Biosensors can also be used to assess the consumption of legal substances (like caffeine, alcohol, or nicotine), medical drugs (antibiotics or opioids), or illicit drugs (cannabis, cocaine, or ecstasy) in the general population (Castiglioni et al. 2015; Gatidou et al. 2016; Ort et al. 2014; Rodríguez-Álvarez et al. 2015; Senta et al. 2015).

These systems detect the presence and magnitude of disease outbreaks more accurately than self-reporting of symptoms, and in a more timely fashion than regular testing (Welling et al. 2022; Wu et al. 2022)—especially when the illnesses have long incubation periods or high prevelance of asymptomatic cases in the population (Toilet Board Commission 2021). Additionally, epidemiological monitoring is less invasive than individual testing. In 2020, for instance, the city of Cambridge, Massachusetts, partnered with Biobot Analytics to set up a network of automatic water sampling bots across the city to study the diffusion of COVID-19 (MIT Underworlds Project n.d.). This COVID-19 surveillance system provided information on a smaller geographical scale compared to wastewater testing at the treatment facility of Deer Island (Toilet Board Commission 2021) and allowed researchers to anticipate the presence of new cases 4-10 days before the emergence of clinical data (Welling et al. 2022; Wu et al. 2022).

Data can be collected at different geographic levels of analysis. Wastewater-Based Epidemiology (WBE) historically has often been conducted at the sewage treatment plant level. However, the development of small and portable sensors allows for the collection of data at a finer scale. For instance, MIT's Underworld project developed automatic wastewater sampling stations that collect data upstream of the sewage plant by placement into manholes around the city, allowing for data collection from smaller communities (MIT Underworlds Project n.d.). Data can also refer to the population of single buildings by placing sampling stations where the building waste enters the municipal sewage system (Duke Center for WaSH-AID--COVID-19 n.d.; MIT Underworlds Project n.d.; Olesen 2021).
These solutions rely on the presence of a sewage system, but in 2020, only 34% of the global population used private sanitation facilities connected to sewers from which wastewater was treated (WHO 2022). In 2019, countries that rank low on the Sustainable Development Index had 8.62% of deaths caused by diarrheal disease, 4.77% by tuberculosis, and 3.46% by HIV/AIDS (IHME n.d.), all conditions whose diffusion could be detected early through WBE.

Therefore, applications in low-resource settings often employ source-point data collected from public latrines. In a pilot project sponsored by the European Space Agency, the Irish company, Woodco Bioscience, tested the feasibility of providing poor communities with public latrines equipped with sensors that infer the prevalence of diseases. The information gathered is sent to a data repository through a cellular data network. Together with weather information and satellite images, the data is used as "inputs to disease early warning models" (Space for Sanitation - Woodco 2020; Toilet Board Coalition n.d.). The system might inform a proactive public health response that precedes and prevents crisis-level outbreaks.

SST for Individual Health Monitoring

Finally, SST can also be used to continuously monitor individual health as opposed to the disease prevalence in a whole community. For instance, the private company Coprata is commercializing a smart toilet developed at Duke University that collects stool samples, automatically capturing data such as "volume, consistency, color, and presence of blood in stools" (Coprata n.d.), all of which are indications of serious ailments, including colon cancer. Researchers at Stanford have developed a smart toilet solution that can automatically perform both urine and stool analysis, and sends the results to a cloud-based health portal accessible to the user and potentially her healthcare provider (Park et al. 2020).

Since multiple household members commonly share toilets, smart toilets need to be able to associate the health data collected with a single individual. There are competing solutions to that end. For instance, Coprata's prototype uses a "QR code and Bluetooth connection via a digital app" to identify the collected samples and data (Coprata n.d.). Park et al. (2020)'s smart toilet is equipped with a fingerprint scan on the flush lever and an anus camera that serves as an analprint scan.

These passive and non-invasive health monitoring systems can be breakthroughs in the prevention of diseases for which early detection drastically improves the chances of recovery. Even though as little as a month delay in treatment can drastically decrease the effectiveness of cancer therapies (Hanna et al. 2020) a 2015 survey shows that only 56.2% of 50-64-year-old men, and 61.2% of women in the same age group, received colon cancer screening in the US (Borsky et al. 2015). Continuous monitoring of waste can compensate for gaps in preventive care. Nevertheless, it is still unclear whether they ultimately lead to better health outcomes.

Policy Guidelines

This section outlines five principles to evaluate SST based on the European Convention on Human Rights, the International Covenant on Civil and Political Rights (ICCPR), and the United Nations Siracusa Principles (which sets the limitations of human rights principles at times of national and international crisis, including public health emergencies). According to this framework, adapted from other applications of technology to public health crises (Morley et al. 2020), the technology has a green light for implementation if:

- there is evidence that it improves outcomes (scientific validity),
- there are no better and less harmful alternatives (necessity),
- social or individual costs are justified by the gravity of the situation (proportionality),
- the deployment plan sets reasonable and realistic sunsetting provisions (time-boundedness), and
- the implementation does not disclose more personal information than an individual might want to share (privacy).

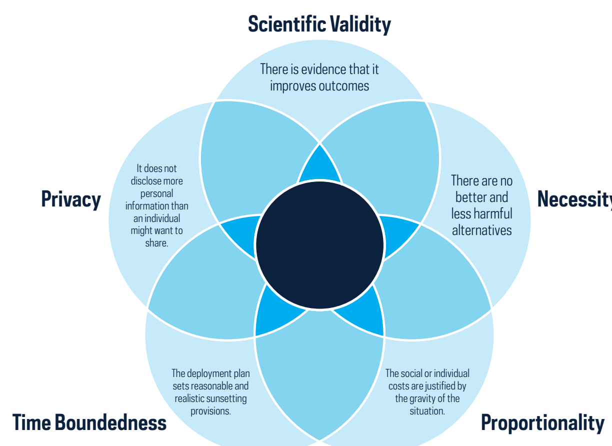

Figure 1: The five conditions that SST must fulfill to justify its adoption.

The following discussion outlines how these broadly accepted principles apply to SST and how policy interventions can be designed to align any type of implementation with these criteria. Figure 2 offers a decision map to check the feasibility of SST implementation for public health purposes based on the previously outlined principles.

Scientific Validity

Scientific validity refers to the availability of evidence that supports the claim that the technology in question can achieve its intended purpose. Two conditions are necessary for this principle to be fulfilled: The first is

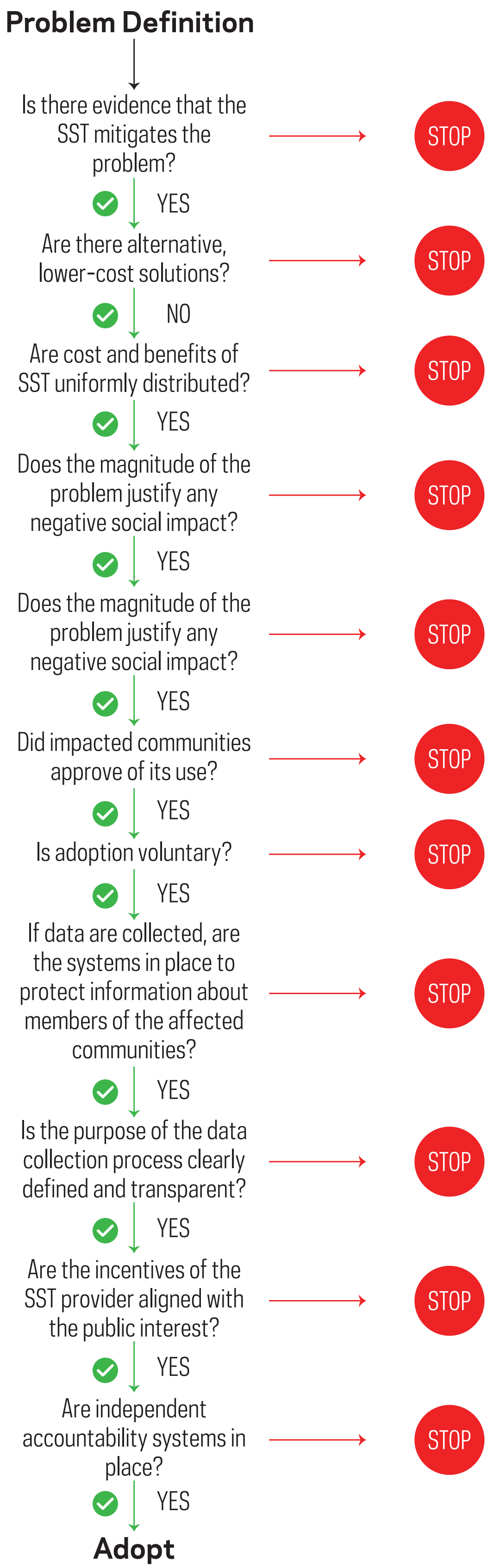

Figure 2: Decision map for the feasibility of SST implementation for public health purposes.

that the technology functions as intended. The second is that it achieves its ultimate objective, in this case, improving health outcomes in the community of reference. Assessing this principle, therefore, requires a combination of insights from multiple disciplines to assess technical feasibility alongside behavioral and social dynamics.

SSTs encompass a wide array of solutions at different levels of development and testing. Therefore, they do not enjoy the same level of evidence of their effectiveness. For example, studies have confirmed that automatic wastewater samplers and subsequent analysis can accurately predict the prevalence of SARS-CoV-2 infections at the neighborhood and residential level with several days of anticipation (Welling et al. 2022; Wu et al. 2022). On the other hand, there is limited evidence that smart toilet solutions can accurately predict the insurgence of diseases outside the sandbox environment of a lab test.

The objective of most of these technologies as they collect community or individual-level data is to provide more abundant or higher-quality information for decision-makers. Nevertheless, more information, especially when hard to interpret, can lead to information overload stifling follow-up action (Khaleel et al. 2020). It is unclear whether the provision of more data, without an effective framework to interpret it, would lead to better health outcomes. If, say, the smart toilet analysis continuously reports a low, but non-zero, probability of ill health, the subject might initiate further health action, or simply get desensitized, discounting the information as irrelevant.

Additionally, the extensive collection of data can lead to seeing patterns in random directions because the machine learning algorithms that analyze them offer probabilistic and non-causal relationships (Blyth 1972; Boyd and Crawford 2012; Valiant 1984). The opacity of machine learning algorithms complicates the recognition of biases (de Laat 2017; Mittelstadt et al. 2016) especially when insights from a particular use or population are applied to different contexts (Danks and John London 2017; Shah 2018).

When spurious conclusions inform policy action, public resources might be misallocated to solutions that do not address the underlying cause of the problem. Suppose that data collected in public latrines displays low levels of water use in a community with high levels of morbidity. That insight might lead policymakers to the conclusion that people are not washing their hands and that health education programs should be introduced. But, the observed behavior might be an adaptation to the low quality of the water in the area. The data were biased, most likely by previous beliefs on the causes of the problem, leading to misleading insight and ineffective responses.

Necessity

Even if the SST in question works as intended, other solutions should be preferred if they either work better or are less harmful. Each technology, therefore, needs to be compared to the ecosystem of solutions available for the problem that it intends to solve. For example, there are very few solutions that allow for non-invasive, daily stool monitoring other than smart toilets. But the absence of similarly functioning products does not imply that the solution is necessary for public health purposes. The objective of smart toilet solutions is arguably not the daily monitoring of stools, but rather how it addresses an identified problem. The problem it is trying to solve might be the early detection of gastrointestinal disease.

Using as a benchmark the public health issue, as opposed to the path taken to address it, we can easily find alternative solutions. Educational programs to self-perform a Bristol stool analysis might be a lower-cost, more equitable, and more privacy-preserving policy approach than, say, subsidizing the development or sale of smart toilets. Free annual check-ups might also serve the same purpose at a lower social cost. To avoid the risk of a "technology for technology's sake" approach, the different solutions considered might include low-tech or non-tech applications that achieve the same end goal. Conversely, SST used for wastewater epidemiological monitoring might prove superior to their alternatives. Self-reports or clinical tests might underestimate the prevalence of diseases, especially when they have long incubation periods and high levels of asymptomatic cases, or when self-reported data is inaccurate due to health-related stigma or shame. Nevertheless, when SSTs are used for public health purposes, assessing the necessity of the application should include a consideration of the action that public authorities would be unable to take in the absence of the technology.

For instance, the detection of opioid use at the local level is useful if resources like educational programs on the risk of drug consumption can be diverted more efficiently depending on the detected prevalence. However, if the high levels of use are driven by medically prescribed uses of opioids, then those programs might be ineffective responses. Therefore, unless alternative public health responses are available, not collecting the data works equally well and is less harmful since it does not give rise to any privacy issue embedded into data collection.

Proportionality

Even when SST is uniquely positioned to deliver established public health benefits, it would be of little use if the social cost of employing that technology outweighs the benefits it provides. In other words, the magnitude of the problem that the SST is set to solve must justify the financial and social cost of addressing it. According to the WHO, every year, the death of 297,000 children under the age of five is connected to diarrheal disease globally (UNICEF and WHO 2019). When considering healthcare costs and loss in economic productivity, the economic burden of diarrheal disease has been estimated to be over $12 billion yearly (Alhamlan, Al-Qahtani, and Al-Ahdal 2015). An illness with such a profound burden might justify a higher social cost than addressing a health issue with a lower impact, like the common cold.

The financial burden of setting up SST solutions is a component of assessing cost. Communities with a higher prevalence of water-borne illness might benefit the most from continuous epidemiological monitoring. Nevertheless, the high cost of SST can often limit the potential for scaling up these solutions after pilot studies, especially given the many competing necessities these communities face.

Not all costs of using these technologies are financial. Many SSTs present important social concerns. The collection of data raises questions of privacy since it might be used to infer sensitive information about individual health. SSTs might exacerbate existing health inequities because wealthier communities might better afford health monitoring systems and higher-income individuals might have easier access to health innovation technologies like smart toilets (Park et al. 2020). The cost and benefits of adopting SSTs might not be uniformly distributed among the population. For example, monitoring HIV prevalence within a city might lead to the over-surveillance and stigma of already vulnerable communities.

Many of the social costs and benefits, however, can be hard to quantify, and therefore compare. How much societies value privacy vis-a-vis the containment of infectious diseases, for example, is difficult to establish and the results likely not to be universal. In those cases, using participatory approaches, either through direct involvement of the affected community or through a mediating entity, can reveal communities' preferences when costs and benefits are subjective and hard to quantify. Participatory approaches are further discussed in the section about privacy.

Time Boundedness

Since a necessary condition of SST deployment is such that the social benefit should outweigh any social cost, there must also be provisions in place to decommission the technology if that balance shifts. Sunsetting provisions are usually set up to prevent that surveillance mechanism initiated to respond to a public health crisis outlive their purpose. For instance, the use of digital "Green Passes" as proof of COVID-19 immunity for visiting public spaces in the European Union required the set up of sunsetting provision to prevent that the use of the system extended beyond crisis-level periods in COVID-19 infections (Beduschi 2021). These provisions usually specify how to define a crisis—and therefore its absence—and how to decommission the technology once it has exhausted its initial objective. But even when the technology is not implemented in response to a crisis, it is important to define ex-ante its intended purpose and the conditions that ground its necessity. One particular challenge is determining the point at which SST technology has exhausted its scope for applications that perform predictive analysis. Consider an SST application that collects data with a descriptive purpose: the information collected alerts health officials of a rise in infections for a given illness, and prompts them to initiate an early public health response. In this case, the SST application itself can provide valuable information on the need for its own decommission. For example, if epidemiological analysis of wastewater reveals the absence of new cases for an extended time, then there might be grounds to scale back monitoring of that particular disease.

For a technology whose purpose is to inform a proactive policy response by predicting disease outbreaks, rather than simply monitoring disease prevalence, sunsetting conditions can be more difficult to establish. Predictive technology can confound the identification of any effect: the absence of disease transmission can be a sign of the system's success and the continuous need for it as much as the possibility of decreased prevalence of the disease. This chicken-and-egg question requires more sophisticated techniques to evaluate the timing of decommissioning, like using proxies of disease prevalence without measuring it directly, or basing the sunsetting decision on comparable locations that do not employ the same SST.

Privacy

Many of the SSTs considered in this paper ultimately collect data about individuals or communities. For example, smart toilets collect individual health information which can be associated with the identity of their users. Sensors in public latrines, on the other hand, cannot connect the information collected to the identity of a single individual but provides a picture of the health status of a whole community.

Both raise questions about data surveillance and privacy. Highly detailed spatial behavior and lifestyle can be inferred from the collected data. Consider, as an example, data on opioid use as tracked through the sewage system. They could be accessed by police and security forces through warrants, be shared with third parties, and might generate analytics with commercial value. Even if they cannot pinpoint use by a single individual, they can create damaging social stigma for those communities that were flagged by the system (Kitchin 2014, 2016).

The collection of data in smart cities has initiated similar debates over the threats and limitations of these data collection processes and uses (Calvo 2019; Kitchin 2014, 2016; Mark and Anya 2019). The use of SST for public health purposes exacerbates these concerns because it often collects sensitive health information. Additionally, most privacy regulations contain language that voids any restrictions during a public health crisis, setting up conditions for the unrestricted use of these technologies. The paragraphs that follow outline some of the privacy considerations for the use of SST. The list includes some major considerations, such as what might constitute consent, the form that a data governance structure might take, the limited purpose of the technology, and that the monitoring systems employed are openly available for public auditing.

Consent

Given the sensitive nature of the information harvested by many SST solutions, citizens should have a say about the data collection process and its use (König 2021). What constitutes as consent to collect and use data depends on the type of technology and its applications. The purchase of a smart toilet might be taken to indicate consent to the collection and the analysis of data since data collection is the primary function of the product. Less clear is the responsibility with respect to a house guest whose data might be collected without that initial purchase decision. The problem could be easily solved, technically, with on and off switches to the sensors that perform the data collection.

Less trivial is the shape that consent should take when the data is collected from public latrines or directly from the sewage system. Those data can build into a probabilistic profile of any individual who lives in the geographical area covered and might contribute to surveillance and stigma. Yet, requiring informed consent to data collection and use from every affected individual might constitute an overly burdensome and unrealistic requirement.

Even when individual consent is feasible, its usefulness has been called into question by the powerful inference tools now available (Kitchin 2016). For example, knowing the sexual orientation of only 20% of social media users enables the prediction of the sexual orientation of others who have not volunteered that information (Baracor and Nissenbaum 2014). This phenomenon, labeled as "tyranny of the minority" renders individual consent relevant only when it is coordinated among users.

Therefore, community preferences for the use of public interest technologies are often assessed by opening public comment periods. In their most simple forms, public comment periods allow any stakeholder to submit input such as opinions, questions, and concerns over the use of a given technology for public purposes. For example, the city of Seattle opened public comments and community town halls over the use of surveillance technology in the city (Seattle IT 2022). Belgium started an open consultation in preparation for the launch of its digital contact tracing app in 2020 (Arseni et al. 2020). While public comments offer a system to increase transparency and democratic legitimacy, they also raise issues of inclusiveness because individuals with a higher level of education and higher incomes might be more likely to submit comments.

Limited Purpose

Suppose that data collected in the sewage system shows that a given area of the city displays higher levels of HIV. That insight is used to inform a more efficient public health response to contain its spread. Should it also be used as an individual risk factor by health insurance companies computing insurance premiums? To prevent abusive and excessive data surveillance, the purpose of the technology and the data collected should be clearly specified before the collection process is initiated. Accountability mechanisms and monitoring agencies should ensure that the limited purpose of the data is not breached.

While this is a legal requirement in many privacy regulations, including the EU's General Data Protection Regulation, it is also of practical relevance. Specifying the intended use of the data can help structure the data collection process effectively and efficiently. It prevents a perspective that takes amassing data as the starting point to later explore what can be done with it, in favor of a problem-centered approach (König 2021). Determining the purpose limitations of the data collection process can be a community exercise that lends democratic legitimacy to the use of the SST.

Conflict of Interest

Many applications of smart city technologies (and possibly of SST) are deployed through a Public-Private Partnership (PPP) model where a private company sells a technological solution to a jurisdiction and (often) subsequently manages it. While PPPs have been celebrated for lending efficiency to public services, misaligned incentives might generate conflicts of interest. Misaligned incentives might trigger a "technology for technology's sake" approach focused on technical fixes that lose track of the problem meant to solve (Carnovale and Louisy 2021). Corporations might use the smart city template as a test bed for new technology to sell their products (Kitchin 2015). Having companies effectively managing cities' public services raises the risk that vested agendas might trump public interest (Mark and Anya 2019). As automatization displaces jobs, the experiential knowledge of the city might be lost, granting greater preponderance to the needs identified by the—potentially biased—data (Mark and Anya 2019). The opacity of many big data analysis techniques exacerbates these problems. If SST solutions are proprietary and held by private companies, the public might be prevented from reviewing the functioning of the SST and assessing any potential bias that might work against the public interest. These shortcomings might harm the perceived democratic legitimacy of SST. Naming independent third parties to routinely assess the effectiveness of the technology in place, with an eye not only on their functioning, but also on the social problem they are set to address, can go a long way when it comes to aligning incentives and ensuring democratic legitimacy to the solution.

Data Governance

Data is never neutral. Even the decision over what type of data is collected and where it is harvested can be driven by substantial levels of bias and have a heterogeneous impact across communities (Kitchin 2016; König 2021). Yet, because of the challenges with obtaining individual consent, the democratic legitimacy of smart city technology has often been called into question, and SST would likely follow a similar path.

A participatory approach based on community autonomy, rather than individual autonomy, might prove better suited when individual consent is hard to collect or meaningless. This approach focuses on setting democratically accepted principles on which the sustainable design of a smart city should be based. These principles should guide the collection and storage of data, their analysis, the achievable insights, the action that they inform, and any other concern that the affected community might rise. While these standards might different across communities, they are meaningful only when accountability mechanisms are designed to translate these principles into formal requirements (König 2021).

Data trusts—intermediary organizations that control city data and are entrusted with protecting the public interest of citizens—have been proposed as solutions to this problem. These organizations can set the standard for the sustainable design and use of smart city technology and initiate monitoring by independent experts to ensure those standards are met by its applications. If democratically elected, data trusts could bestow legitimacy to the application of the public interest technology they oversee. Finally, bestowing on data trusts the responsibility over the collection, use, and sharing of data effectively brings the ownership of the extracted data onto the citizenry as opposed to private companies or governments (Delacroix and Lawrence 2019; König 2021; Mills 2019; O'hara 2019).

Data trusts and participatory approaches are not a panacea. Participatory approaches are time-consuming and their output might ultimately only represent the view of the most influential members of a community, or those with more resources to take part in the debate. They can also be influenced by power dynamics, and foster power struggles within communities. Data trusts are not immune to manipulation, and the risk is higher in countries where corruption is rampant (Transparency International 2021). Data governance structures should therefore remain fully transparent so that individuals, the press, and civil society organizations can investigate and denounce any perceived abuses.

Conclusions

SST promises to expedite wastewater-based epidemiological analysis, monitor the status and use of the sanitation infrastructure and automatize its maintenance, and track individual health trends. Despite the presence of some case studies, its public health potential (and possible threat) is unfamiliar territory for practitioners and researchers alike. While SST might sustain the vision of the UN Sustainable Development Goals, it can also lead the continuous surveillance of individual existence—an often criticized feature of smart city architecture—to an incredibly intimate location: the toilet. The data collected by many SST applications can be considered health data. Their improper use can generate harm and stigma. Whether SST can create value for its citizenry will largely depend on the design of a sound policy ecosystem behind its use.

In this paper, I outline considerations for stakeholders to make informed decisions and carefully weigh opportunities and threats that arise from the use of SST for public health purposes. It outlines some basic and uncontroversial policy principles that should guide any on-the-ground implementation of SST. Those principles include scientific validity, necessity, proportionality, time-boundedness, and privacy. This list is far from comprehensive, but it is an initial approach to an emerging industry with enormous potential for achieving sustainable development objectives under the condition that ethical considerations are addressed appropriately.

Many of the recommendations outlined stem from a larger debate on the social impact of smart city technology and its policy implications. SST, however, presents some challenges that are unique within smart city architecture. It collects data that pertain to individual or communities' health which qualifies as sensitive information. Many privacy legislations contain language that void any privacy requirement during a public health crisis, heightening the potential for abuses unless the SST implemented encapsulates these policy principles in its design. A sound policy ecosystem includes the creation of a host of accountability mechanisms that can lend ethical soundness and democratic legitimacy to the use of SST for public health purposes.

Failure to do so might result in SST doing more harm than good. Other technologies have had similar fates. The facial recognition technology that was supposed to increase the safety of cities ended up criminalizing vulnerable communities (Cowling 2021; Petty 2020; Williams 2020). The mortgage algorithms that were supposed to end racial biases in the provision of loans ultimately excacerbated those biases (Rice and Swesnik 2013; Townson 2020). Fear of unintended effects or policy backlash might discourage the adoption of SST altogether, preventing the realization of their potential to support public health goals.

References

Alhamlan, Fatimah S., Ahmed A. Al-Qahtani, and Mohammed N. Al-Ahdal. 2015. "Recommended Advanced Techniques for Waterborne Pathogen Detection in Developing Countries." The Journal of Infection in Developing Countries 9(02): 128–35. https://www.jidc.org/index.php/journal/article/view/6101 (December 7, 2021).

Arseni, Maurizio, Maria Carnovale, Augusto Gesualdi, and Laura Murphy. 2020. "Can a Global NGO Make Digital Contact Tracing Work?" Issues in Science and Technology. https://issues.org/global-ngo-digital-contact-tracing-covid-pandemic/ (November 22, 2022).

Baracor, S, and H Nissenbaum. 2014. "Big Data's End Run around Anonymity and Consent." In Privacy, Big Data and the Public Good, eds. J Lane, V Stodden, S Bender, and H Nissenbaum. Cambridge, UK: Cambridge University Press, 44–75.

Beduschi, Ana. 2021. Covid-19 Health Status Certificates: Policy Recommendations on Data Privacy and Human Rights. University of Exeter College of Social Sciences and International Studies. https://ore.exeter.ac.uk/repository/handle/10871/126946 (December 19, 2022).

"Biobot Analystics, Inc. - Homepage." https://biobot.io/ (November 9, 2021).

Blyth, Colin R. 1972. "On Simpson's Paradox and the Sure-Thing Principle." Journal of the American Statistical Association 67(338): 364–66.

Borsky, Amanda E. et al. 2015. Medical Expenditure Panel Survey Use of Clinical Preventive Services in the United States: Estimates from the Medical Expenditure Panel Survey (MEPS), 2015. https://meps.ahrq.gov/data_files/publications/rf41/rf41.shtml (November 9, 2022).

Boyd, Danah, and Kate Crawford. 2012. "Critical Questions for Big Data." Information, Communication and Society 15(5): 662–79. http://www.tandfonline.com/loi/rics20http://dx.doi.org/10.1080/1369118X.2012.678878 (November 18, 2022).

Calvo, Patrici. 2019. "The Ethics of Smart City (EoSC): Moral Implications of Hyperconnectivity, Algorithmization and the Datafication of Urban Digital Society." Ethics and Information Technology 2019 22:2 22(2): 141–49. https://link.springer.com/article/10.1007/s10676-019-09523-0 (November 1, 2022).

Carnovale, Maria, and Khahlil Louisy. 2021. "Public Health, Technology, and Human Rights: Lessons Learned from Digital Contact Tracing." Carr Center Discussion Paper Series.

Castiglioni, Sara et al. 2015. "A Novel Approach for Monitoring Tobacco Use in Local Communities by Wastewater Analysis." Tobacco Control 24(1): 38–42. https://tobaccocontrol.bmj.com/content/24/1/38 (November 9, 2022).

City of Cambridge MA. 2020. "New Partnership Tracks COVID-19 Infections in Cambridge by Analyzing Wastewater." Press Release. https://www.cambridgema.gov/covid19/News/2020/11/newpartnershiptrackscovid19infectionsincambridgebyanalyzingwastewater (November 16, 2021).

"Coprata." https://coprata.com/ (November 9, 2022).

Costa, Daniel G. 2020. "Visual Sensors Hardware Platforms: A Review." IEEE Sensors Journal 20(8): 4025–33.

Cowling, Mark. 2021. "Artificial Intelligence and the Criminalisation of Activism." Criminalization of Activism: 207–15. https://www.taylorfrancis.com/chapters/edit/10.4324/9781003144229-25/artificial-intelligence-criminalisation-activism-mark-cowling (December 8, 2022).

Dai, Chengzhen L. et al. 2019. "Multi-Site Sampling and Risk Prioritization Reveals the Public Health Relevance of Antibiotic Resistance Genes Found in Wastewater Environments." bioRxiv: 562496. https://www.biorxiv.org/content/10.1101/562496v1 (November 9, 2021).

Danks, David, and Alex John London. 2017. "Algorithmic Bias in Autonomous Systems." Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence. https://www.bls.gov/cps/cpsaat11.htm]. (November 18, 2022).

Delacroix, Sylvie, and Neil D. Lawrence. 2019. "Bottom-up Data Trusts: Disturbing the 'One Size Fits All' Approach to Data Governance." International Data Privacy Law 9(4): 236–52. https://academic.oup.com/idpl/article/9/4/236/5579842 (November 20, 2022).

"Duke Center for WaSH-AID--COVID-19." Duke University Pratt School of Engineering. http://washaid.pratt.duke.

edu/covid-19 (September 11, 2022).
Garv. “Projects | Garv Toilets- The Future of Public Sanitation.” http://www.garvtoilets.com/projects.html (November 7, 2022).
Gatidou, Georgia et al. 2016. “Drugs of Abuse and Alcohol Consumption among Different Groups of Population on the Greek Island of Lesvos through Sewage-Based Epidemiology.” Science of The Total Environment 563–564: 633–40.
Ghayvat, Hemant, Sharnil Pandya, and Ashish Patel. 2020. “Deep Learning Model for Acoustics Signal Based Preventive Healthcare Monitoring and Activity of Daily Living.” 2nd International Conference on Data, Engineering and Applications, IDEA 2020.
Gill, Victoria. 2021. “Covid-19: Sewage Testing Ramped Up in England - BBC News.” BBC. https://www.bbc.com/news/science-environment-57205126 (November 16, 2021).
Goodridge, Lawrence. 2020. “Sewage Surveillance: How Scientists Track and Identify Diseases like COVID-19 before They Spread.” The Conversation. https://theconversation.com/sewage-surveillance-how-scientists-track-and-identify-diseases-like-covid-19-before-they-spread-148307 (November 16, 2021).
GSMA. 2017. “Kampala Capital City Authority | Mobile for Development.” GSMA. https://www.gsma.com/mobilefordevelopment/mgrantee/kampala-capital-city-authority/ (November 30, 2022).
Hanna, Timothy P. et al. 2020. “Mortality Due to Cancer Treatment Delay: Systematic Review and Meta-Analysis.” BMJ 371: m4087. https://www.bmj.com/content/371/bmj.m4087 (November 20, 2022).
Hellmér, Maria et al. 2014. “Detection of Pathogenic Viruses in Sewage Provided Early Warnings of Hepatitis A Virus and Norovirus Outbreaks.” Applied and environmental microbiology 80(21): 6771–81. https://pubmed.ncbi.nlm.nih.gov/25172863/ (November 16, 2021).
Hovi, T., M. Stenvik, H. Partanen, and A. Kangas. 2001. “Poliovirus Surveillance by Examining Sewage Specimens. Quantitative Recovery of Virus after Introduction into Sewerage at Remote Upstream Location.” Epidemiology & Infection 127(1): 101–6. https://www.cambridge.org/core/journals/epidemiology-and-infection/article/poliovirus-surveillance-by-examining-sewage-specimens-quantitative-recovery-of-virus-after-introduction-into-sewerage-at-remote-upstream-location/EB531F077E4C87FD7284B143352EEEAD (November 22, 2022).
Hutton, Guy. 2013. “Global Costs and Benefits of Reaching Universal Coverage of Sanitation and Drinking-Water Supply.” J Water Health 11(1). https://iwaponline.com/jwh/article/11/1/1/2773/Global-costs-and-benefits-of-reaching-universal (November 9, 2021).
IHME. “Global Burden of Disease Data.” The Lancet. https://www.thelancet.com/lancet/visualisations/gbd-compare.
Impouma, Benido et al. 2020. “Measuring Timeliness of Outbreak Response in the World Health Organization African Region, 2017–2019.” Emerging Infectious Diseases 26(11): 2555–64. https://wwwnc.cdc.gov/eid/article/26/11/19-1766_article (November 16, 2021).
Kim, Jayoung, Alan S. Campbell, Berta Esteban Fernández de Ávila, and Joseph Wang. 2019. “Wearable Biosensors for Healthcare Monitoring.” Nature Biotechnology 2019 37:4 37(4): 389–406. https://www.nature.com/articles/s41587-019-0045-y (November 7, 2022).
Kitchin, Rob. 2014. “The Real-Time City? Big Data and Smart Urbanism.” GeoJournal 79(1): 1–14. https://link.springer.com/article/10.1007/s10708-013-9516-8 (November 1, 2022).
———. 2015. “Data-Driven, Networked Urbanism.” SSRN Electronic Journal. https://papers.ssrn.com/abstract=2641802 (November 20, 2022).
———. 2016. “The Ethics of Smart Cities and Urban Science.” Philos Trans A Math Phys Eng Sci 374(2083). https://doi.org/10.1098/rsta.2016.0115.
König, Pascal D. 2021. “Citizen-Centered Data Governance in the Smart City: From Ethics to Accountability.” Sustainable Cities and Society 75: 103308.
De La Rica, Roberto, and Molly M. Stevens. 2012. “Plasmonic ELISA for the Ultrasensitive Detection of Disease Biomarkers with the Naked Eye.” Nature Nanotechnology 2012 7:12 7(12): 821–24. https://www.nature.com/articles/nnano.2012.186 (November 7, 2022).
de Laat, Paul B. 2017. “Algorithmic Decision-Making Based on Machine Learning from Big Data: Can Transparency

Restore Accountability?" Philosophy & Technology 2017 31:4 31(4): 525–41. https://link.springer.com/article/10.1007/s13347-017-0293-z (November 22, 2022).
Lucarelli, F. et al. 2002. "Electrochemical DNA Biosensor for Analysis of Wastewater Samples." Bioelectrochemistry 58(1): 113–18.
Maraldo, David, Fernando U. Garcia, and Raj Mutharasan. 2007. "Method for Quantification of a Prostate Cancer Biomarker in Urine without Sample Preparation." Analytical Chemistry 79(20): 7683–90. https://pubs.acs.org/doi/abs/10.1021/ac070895z (November 7, 2022).
Mark, Ryan, and Gregory Anya. 2019. "Ethics of Using Smart City AI and Big Data: The Case of Four Large European Cities." The ORBIT Journal 2(2): 1–36.
Mills, Stuart. 2019. "Who Owns the Future? Data Trusts, Data Commons, and the Future of Data Ownership." SSRN Electronic Journal. https://papers.ssrn.com/abstract=3437936 (November 20, 2022).
"MIT Underworlds Project." Senseable City Lab. http://underworlds.mit.edu/ (September 11, 2022).
Mittelstadt, Brent Daniel et al. 2016. "The Ethics of Algorithms: Mapping the Debate." Big data & Society 3(2). http://dx.doi.org/10.1177/2053951716679679 (November 22, 2022).
Morais, Cat, and Leonard Kore. 2020. "Kampala Capital City Authority – Unlocking the Power of Mobile-Enabled Sanitation." GSMA. https://www.gsma.com/mobilefordevelopment/blog/kampala-capital-city-authority-unlocking-the-power-of-mobile-enabled-sanitation/ (November 9, 2022).
Morley, Jessica, Josh Cowls, Mariarosaria Taddeo, and Luciano Floridi. 2020. "Ethical Guidelines for COVID-19 Tracing Apps." Nature 582(7810): 29–31. https://www.nature.com/articles/d41586-020-01578-0 (April 7, 2021).
Muscillo, M. et al. 2013. "GIV Noroviruses in Wastewaters and in Stool Specimens from Hospitalized Patients." Food and Environmental Virology 5(4): 194–202. https://link.springer.com/article/10.1007/s12560-013-9121-5 (November 22, 2022).
Newton, Ryan J. et al. 2015. "Sewage Reflects the Microbiomes of Human Populations." mBio 6(2). https://pubmed.ncbi.nlm.nih.gov/25714718/ (November 7, 2022).
O'hara, Kieron. 2019. "Data Trusts: Ethics, Architecture and Governance for Trustworthy Data Stewardship." University of Southampton Institutional Repository.
Olesen, Scott. 2021. Interpreting Building-Level Covid-19 Wastewater Monitoring Data. figshare. /articles/preprint/Interpreting_building-level_Covid-19_wastewater_monitoring_data/16587068/1 (November 9, 2022).
Ort, Christoph et al. 2014. "Spatial Differences and Temporal Changes in Illicit Drug Use in Europe Quantified by Wastewater Analysis." Addiction 109(8): 1338–52.
Park, Seung-min et al. 2020. "A Mountable Toilet System for Personalized Health Monitoring via the Analysis of Excreta." Nature biomedical engineering 4(6): 624–35. https://pubmed.ncbi.nlm.nih.gov/32251391/ (November 9, 2022).
Petty, Tawana. 2020. "Defending Black Lives Means Banning Facial Recognition." WIRED. https://www.wired.com/story/defending-black-lives-means-banning-facial-recognition/ (December 8, 2022).
Rary, Emma et al. 2020. "Smart Sanitation-Biosensors as a Public Health Tool in Sanitation Infrastructure." International Journal of Environmental Research and Public Health 17(14): 1–14. https://pubmed.ncbi.nlm.nih.gov/32708793/ (November 16, 2021).
Rice, Lisa, and Deidre Swesnik. 2013. "Discriminatory Effects of Credit Scoring on Communities of Color." Suffolk University Law Review. http://www.remappingdebate.org/map-data-tool/new-maps-show-segregation-alive-and-well (December 8, 2022).
Riordan, John T. 1962. "Isolation of Enteroviruses from Sewage Before and After Vaccine Administration." Yale Journal of Biology and Medicine 34. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2604391/pdf/yjbm00614-0082.pdf (November 22, 2022).
Rodríguez-Álvarez, Tania et al. 2015. "Alcohol and Cocaine Co-Consumption in Two European Cities Assessed by Wastewater Analysis." Science of The Total Environment 536: 91–98.
Seattle IT. 2022. "Public Comment Period Opening for Technologies Subject to the City's Surveillance Ordinance." Tech Talk. https://techtalk.seattle.gov/2022/04/18/public-comment-period-opening-for-technologies-sub-

ject-to-the-citys-surveillance-ordinanc/ (November 22, 2022).
Senta, Ivan et al. 2015. "Wastewater Analysis to Monitor Use of Caffeine and Nicotine and Evaluation of Their Metabolites as Biomarkers for Population Size Assessment." Water Research 74: 23–33.
Shah, Hetan. 2018. "Algorithmic Accountability." Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 376(2128). https://royalsocietypublishing.org/doi/10.1098/rsta.2017.0362 (November 18, 2022).
Sharif, Nadim et al. 2020. "Molecular and Epidemiologic Analysis of Diarrheal Pathogens in Children with Acute Gastroenteritis in Bangladesh during 2014-2019." Pediatric Infectious Disease Journal: 580–85.
Song, Yi Zhe et al. 2014. "Virtual Visual Sensors and Their Application in Structural Health Monitoring." Structural Health Monitoring 13(3): 251–64. http://dx.doi.org/10.1177/1475921714522841 (November 22, 2022).
"Space for Sanitation - Woodco." 2020. European Space Agency (ESA) Business Applications. https://business.esa.int/projects/space-for-sanitation-woodco (October 24, 2022).
Toilet Board Coalition. 2018. Smart Sanitation City: A Thought Piece from the Toilet Board Coalition in Partnership with the Pune Municipal Corporation and Pune Smart City, India. https://www.toiletboard.org/media/45-TBC_2018PuneReport_11202018.pdf?v=1.0.1 (November 9, 2021).
———. "Case Study: Smart Sanitation & Digital Water: Woodco." Toilet Board Coalition. https://www.toiletboard.org/smart-sanitation-digital-water-woodco/ (November 22, 2022).
Toilet Board Coalition (2021). Improving Public Health Through Smart Sanitation and Digital Water How Data Ecosystems and Wastewater Epidemiology Can Play a Larger Role. https://iwa-network.org/wp-content/uploads/2020/11/Improving-Public-Through-Smart-Sanitation-and-Digital-Water-IWA-TBC.pdf
Townson, Sian. 2020. "AI Can Make Bank Loans More Fair." Harvard Business Review. https://hbr.org/2020/11/ai-can-make-bank-loans-more-fair (December 8, 2022).
Transparency International. 2021. "2021 Corruption Perceptions Index." Transparency International . https://www.transparency.org/en/cpi/2021 (December 9, 2022).
Tumwine, James K. et al. 2002. "Diarrhoea and Effects of Different Water Sources, Sanitation and Hygiene Behaviour in East Africa." Tropical Medicine & International Health 7(9): 750–56. https://onlinelibrary.wiley.com/doi/full/10.1046/j.1365-3156.2002.00927.x (December 2, 2022).
UNICEF. 2021. "Sanitation Statistics." UNICEF DATA. https://data.unicef.org/topic/water-and-sanitation/sanitation/ (December 8, 2022).
UNICEF, and WHO. 2019. "1 in 3 People Globally Do Not Have Access to Safe Drinking Water." https://www.who.int/news/item/18-06-2019-1-in-3-people-globally-do-not-have-access-to-safe-drinking-water-unicef-who (December 7, 2021).
Valiant, L. G. 1984. "A Theory of the Learnable." Communications of the ACM 27(11): 1134–42. https://dl.acm.org/doi/10.1145/1968.1972 (November 18, 2022).
Webster, Thaddaeus A. et al. 2014. "Electrochemical Detection of Pseudomonas Aeruginosa in Human Fluid Samples via Pyocyanin." Biosensors and Bioelectronics 60: 265–70.
Welling, Claire M. et al. 2022. "Predictive Values of Time-Dense SARS-CoV-2 Wastewater Analysis in University Campus Buildings." Science of The Total Environment 835: 155401.
WHO. 2019. Safer Water, Better Health. Geneva. https://www.who.int/publications/i/item/9789241516891.
———. 2022. "Sanitation." World Health Organization. https://www.who.int/news-room/fact-sheets/detail/sanitation (November 15, 2022).
Williams, Damien Patrick. 2020. "Fitting the Description: Historical and Sociotechnical Elements of Facial Recognition and Anti-Black Surveillance." https://doi.org/10.1080/23299460.2020.1831365 7(S1): 74–83. https://www.tandfonline.com/doi/abs/10.1080/23299460.2020.1831365 (December 8, 2022).
World Health Organization, and United Nations Economic Commission for Europe. 2019. Surveillance and Outbreak Management of Water-Related Infectious Diseases Associated with Water-Supply Systems. http://apps.who.int/bookorders. (November 9, 2021).
Wu, Fuqing et al. 2022. "SARS-CoV-2 RNA Concentrations in Wastewater Foreshadow Dynamics and Clinical Pre-

sentation of New COVID-19 Cases." Science of The Total Environment 805: 150121.
Yang, Zhugen et al. 2015. "Community Sewage Sensors for Monitoring Public Health." Environmental Science and Technology 49(10): 5845–46. https://pubs.acs.org/doi/full/10.1021/acs.est.5b01434 (November 3, 2022).

Appendix A: Checklist and Decision Map for Practical Implementation

The following checklist outlines how these broadly accepted principles might be applied to evaluate the adoption of a chosen SST solution.

1) What is the public health issue that the SST under consideration is meant to solve?

The use of SST is justifiable when it addresses a clearly defined public health issue. The problem should be framed in terms of the social outcome to address rather than the lack of resources to face it. For instance, a shortage of public latrines and consequent open defecation might not be, per se, a public health issue. That is the mechanism for the spread of infections and potential disease outbreaks: the identified public health concern. In this example, increasing the number or quality of public latrines is the identified solution to the disease outbreak problem. The identified purpose of the SST will serve as a benchmark for subsequent considerations.

2) Is there sufficient scientific evidence that the SST under consideration solves or mitigates the previously identified problem?

✅ Yes, the SST works effectively and is an evidenced-based solution: scientific studies have connected its use to the improvement of public health metrics.

✅ No, the SST is still in its piloting phase and while there is evidence that it functions appropriately, no studies have connected its use to health or social outcomes.

❌ No, there is no scientific evidence showing that the use of the considered SST improves the health metrics connected to the public health interest that it serves.

3) Are there alternative solutions to address the same public health issues at a lower financial and social cost?

✅ No, this is the lowest-cost solution to the identified public health problem.

❌ Yes, alternative solutions that impose a lower social impact on the affected individuals or communities exist and are available.

4) Are the social costs and benefits associated with the use of the SST under consideration uniformly distributed across the population?

✅ Yes, the technology is equally available to and easy to use for all individuals in the impacted communities, and it benefits all members of the community equally.

✅ No, some communities or individuals bear more of the social or financial cost of the technology, but they also benefit the most from its implementation because of underlying health vulnerabilities.

❌ No, some communities disproportionally bear the burden of the SST implementation (through increased health surveillance, criminalization, stigma, diminished privacy,…)

5) Does the gravity of the public health issue justify the SST's negative social impact?

✅ Yes, the social benefits of the SST outweigh its cost for all the individuals impacted. Provisions mitigate any negative impact on the communities who are disproportionately impacted and establish remedial action.

❌ No, social costs outweigh any social benefit for the majority of the population or the magnitude of the negative social impact is so high for an affected minority that any meaningful remediation is unfeasible.

6) Are there sunsetting provisions to the SST under consideration?

✅ Yes, provisions are in place to decommission the technology when the public health issue that it serves is no longer present. Public health indicators are consistently monitored to ensure that the decommissioning process is initiated when needed.

❌ No, no end date is established for its use.

7) Do people have a choice over the adoption or design of the SST under consideration?

✅ Yes, the consent of the impacted individuals is solicited before adopting the technology. When individual consent is unfeasible, meaningful solutions are in place to include the impacted communities' voices in the SST's adoption decision-making process.

❌ No, the use of the SST is mandatory and /or imposed with little to no review by the most impacted communities.

8) Is the use of the SST under consideration voluntary?

✅ Yes, the use of the SST is optional.

✅ No, the use of the SST is mandatory, but it has been explicitly and meaningfully approved by the impacted community.

✅ Yes, the use of the SST is optional, but some individuals might not have easy access to alternatives.

❌ No, use of the SST is mandatory and/or imposed with little to no review by the most impacted communities.

9) If data are collected, are there systems in place to protect information about members of the affected communities?

✅ Yes, the collection, analysis, and sharing of the data collected preserve the privacy of the individuals who have consented to the data collection process. Systems are also in place to protect any information on individuals or communities that might be inferred from the collected data, independently of prior consent.

❌ No, cyber-security is low and data use is unresponsible. For instance, the data are identifiable or re-identifiable, they are easily accessible to non-authorized entities, and inferences on private information of individuals who have not expressed consent to the data collection process are used without their knowledge or consent.

10) Is the purpose of the data collection process clearly defined and transparent?

✅ Yes, data cannot be applied to any use other than what was explicitly communicated when consent was solicited or the use of the SST approved by the impacted community.

❌ No, the data is amassed as the starting point to later explore what can be done with it. The purpose limitation is excessively broad and does not provide adequate transparency over data uses.

11) Are the incentives for the entity selling the SST, managing it, or analyzing its data aligned with the public interest it serves?

✅ Yes, compensation and accountability systems ensure that the SST or its data is not used to the detriment of the impacted community.

❌ No, the entities selling or managing the technology might be subject to conflicts of interest.

12) Are independent accountability systems in place to monitor that the previous conditions are continuously met?

✅ Yes, participatory governance mechanisms are in place to monitor the use of the technology, provide independent evaluations of its effect and ensure that the limitations agreed upon apply to any SST application.

❌ No, there is no organization or public entity with the explicit mandate to monitor the use of the SST.

PULTE INSTITUTE
FOR GLOBAL DEVELOPMENT

pulte.nd.edu

3150 Jenkins Nanovic Halls
Notre Dame, Indiana 46556 USA
(574) 631-2940

globaldevelopment@nd.edu