

# Integrating Wastewater-Based Epidemiology (WBE) With Predictive Analytics For Tracking Non-Communicable Diseases (Ncds) In Urban Populations

Ayman Mokhaider Atiah Alhojely<sup>1</sup>, Alaa Mohammed Ali Alsaggaf<sup>1</sup>, Bahiah Abdulaziz Abdulhamid Kurdi<sup>1</sup>, Mai Ahmed Salem Hubaysh<sup>2</sup>, Tariq Omar Abdullah Ali<sup>2</sup>, Husam Majid Shahada<sup>2</sup>, Ghadah Mabruk Saeed Alharbi<sup>2</sup>, Naif Habib Eid Alsaadi<sup>2</sup>, Fahad Ayed Alharbi<sup>2</sup>, Wael Waleed Ballaji<sup>2</sup>, Hani Mohammad Al-Harbi<sup>2</sup>, Shareefah Ahmad Alzahrani<sup>3\*</sup>, Salha Difallah Althobiti<sup>3</sup>, Layla Tahseen Naseeb Almowald<sup>3</sup>, Omar Hamed Alsalemi<sup>4</sup>, Ramy Abdullah Badawy<sup>4</sup>

<sup>1</sup>King Salman Bin Abdulaziz Medical City-Madinah, Al-Madinah 42319, Saudi Arabia

<sup>2</sup>Ohud Hospital-Madinah, As Salam-7118, Medinah-42354, Saudi Arabia

<sup>3</sup>Makkah Healthcare Cluster, Ministry of Health, Makkah 24246, King Abdulaziz Hospital, Saudi Arabia

<sup>4</sup>Madinah Health Cluster, Ministry of Health, Iaa-7011, Pobox 4102, Madinah 42325, Saudi Arabia

\*Corresponding author: shahalzhrani@moh.gov.sa

## Abstract

Convergence of Wastewater-Based Epidemiology (WBE) and predictive analytics, opens up to new approaches to public health surveillance. WBE has been practiced throughout history as a tool to trace infectious diseases and monitor the community's health via biomarkers identified in the wastewater. The potential in future research regarding WBE escalates exponentially considering the COVID-19 pandemic has come to show what a low-cost, non-invasive tool gives real-time information about disease dynamics at the level of the community. In this parallel, it will be huge data analytics as predictive analytics, applied to track health trends along with resource allotment with a public health intervention. Such an integrated framework will emerge if these methodologies are integrated together; it could be used for NCD surveillance, which is yet one of the major challenges in global health. The integrated approach could find a biomarker for NCDs, monitor lifestyle factors, and predict prevalence to allow timely interventions. Data standardization, privacy concerns, and methodological differences create challenges toward its equitable and effective implementation. In this regard, this review would discuss how the synergy of WBE with predictive analytics can support applications in monitoring NCD, highlight the application fields, and focus on operational and ethical issues regarding this integration. Public health systems can, therefore, improve disease surveillance and public health outcomes by leveraging the strengths of both disciplines to better address urban health disparities.

**Keywords** Wastewater-Based Epidemiology, Predictive Analytics, Non-Communicable Diseases, Public Health Surveillance, Urban Health, Biomarkers, Data Integration, Health Disparities.

## 1. Introduction

### 1.1. Overview of Wastewater-Based Epidemiology (WBE)

Wastewater-based epidemiology, from being a niche research area in the last few decades to now being emphasized as an important public health tool, particularly in the case of the COVID-19 pandemic. The use of wastewater as a monitoring tool for epidemiological surveillance goes back to the early 2000s when it

was first noticed that the analysis of wastewater would possibly reflect the status of health of the community because of the presence of pathogens and chemical substances. This has therefore been useful in surveillance of infectious diseases, illicit drug use, among other public health issues. This initial application of WBE was mainly for the identification of some specific pathogens, for example, poliovirus and hepatitis A excreted into human waste. Early work in the field indicated that wastewater was an information reservoir for health status within populations and therefore could be employed to provide early outbreak detection and surveillance on the prevalence of disease. For instance, the estimation of viral RNA in wastewater has been shown to provide insights into the transmission dynamics of viruses in communities and, as such, timely public health response (Miyani et al., 2020; Rao, 2024). This has been advanced to ranges of pathogens and substances, such as bacteria, parasites, and chemical analytes associated with drug use (Li et al., 2020; Rousis et al., 2017).

Molecular advancements, especially qPCR, have improved the potential of WBE. These methods are sensitive and specific for detecting viral RNA, such as that of SARS-CoV-2, the causative agent of COVID-19. Their application during the pandemic era has underlined the utility of WBE, which offers real-time community transmission data, enabling public health practitioners to make the appropriate decisions on intervention and resource use (Fontenele et al., 2021; Joseph-Duran et al., 2022; Agrawal et al., 2021). It has been further validated through correlating wastewater data with clinical case numbers that WBE can be an even stronger tool in surveillance (Daughton, 2020). The recent breakthroughs in high-throughput sequencing technologies have opened several avenues to explore the genetics of diversity in pathogens in wastewater. This has served scientists with the avenue to track circulating variants of viruses, including SARS-CoV-2, which is key in the comprehension of infectious diseases' evolution and spread (Fontenele et al., 2021; Joseph-Duran et al., 2022). Spatial and temporal analysis of wastewater-derived sequences has recently emerged as fundamental for bettering the understanding of disease dynamics in the community at large in contemporary epidemiological analysis (Rao, 2024; Agrawal et al., 2021).

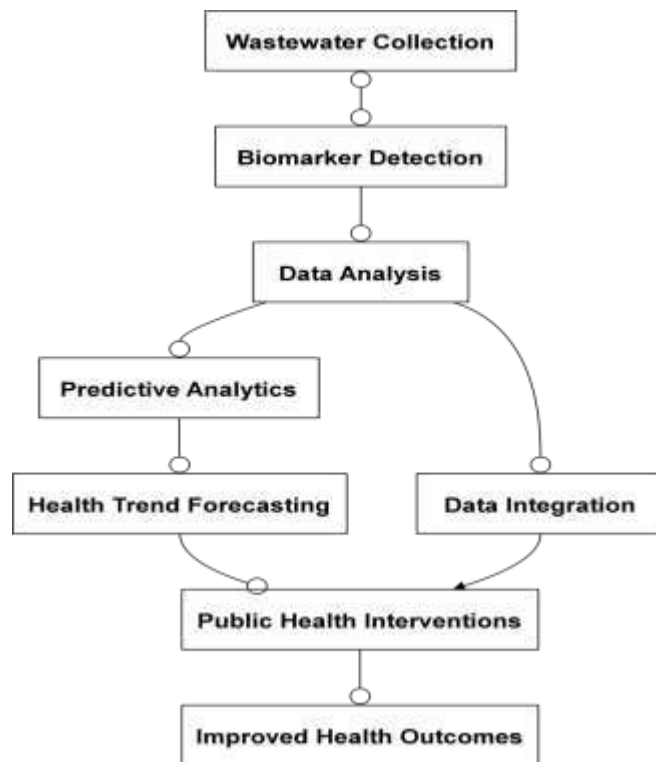
The other historical context involves the use of WBE to track illegal consumption of drugs, among other environmental pollutants. The early research in WBE encompasses the identification of drugs in wastewater, which provides much insight into community consumption patterns and their associated public health concerns (Li et al., 2020; Rousis et al., 2017). Considering the rapid emergence of global health pandemics, no better time existed for WBE to show significance than in current times. Its potential has proven through a renewed wave of scientific research and practice with COVID-19. Through its use as an early warning system, its capability in detection of emerging infectious diseases is becoming increasingly clear. The rapid adaptation of WBE methodologies in monitoring SARS-CoV-2 has thrown light on the flexibility and responsiveness of this approach to address urgent public health needs (Joseph-Duran et al., 2022; Daughton, 2020). Co-operation from the research, health professionals and the politicians has given room to better-coordinated diseases' surveillance from time to time; nowadays epidemiology has stressed its major concern at the WBE.

Wastewater-based epidemiology, or WBE, has recently become a very important tool in monitoring infectious diseases, especially after the COVID-19 pandemic. This new approach to sampling pathogens from wastewater enables researchers to find out about the health status of a community without relying solely on clinical testing or healthcare-seeking behaviors. Besides the instances of COVID-19, according to a research study by Neyra (2023) and Rainey et al. (2022), as well as Naik (2023), WBE has also become a good surrogate for tracking several other pathogens: poliovirus, hepatitis, norovirus, and salmonellosis. This offers an opportunity to track viral loads in wastewater, where symptomatic and asymptomatic carriers can be followed, thus offering a fuller picture of disease prevalence in the populace (Naik, 2023; Kumar et al., 2020).

WBE use in real-time surveillance in the case of the COVID-19 pandemic proved to be effective compared to clinical metrics, such as the number of cases and hospital admissions (Mao et al., 2020; Gazeley, 2024). It has been recently reported that the concentrations of SARS-CoV-2 in wastewater are positively correlated with reported cases of COVID-19; also, a recommendation has come that WBE may be developed into an early warning system of outbreaks (Mao et al., 2020; Gazeley, 2024). This application will be very helpful in the densely populated areas where conventional surveillance methods will be limited due to lack of access to health care or testing resources. Additionally, WBE can be a cost-effective and proactive approach for the detection of emerging pathogens at the community level, thus improving public health responses (Rainey et al., 2022; Naik, 2023).

This heritage is based on the flexibility of WBE for changing pathogens and its possible utility for more expanded public health surveillance. History also reveals that it has been there for decades being used for the surveillance of infectious diseases from when it was initially applied to typhoid and poliovirus in the beginning of the 20th century (Kantor et al., 2022; Naik, 2023). With the evolution of the paradigm in infectious diseases, lessons learned from WBE could be applied in NCD since it is now the fastest rising part of public health burden and is prevalent worldwide.

Applicable principle of WBE will encompass the following, such as; biomarkers monitoring in water waste towards inferring cases like diabetes and cardiovascular disease with several types of cancer. For example, indirect surrogates of health behavior or disease prevalence in the community can be certain metabolites or drugs due to their presence in wastewater (Matra, 2024). That would suggest at-risk populations and interventions could be better targeted-though WBE has already been applied to infectious diseases. The integration of WBE data with other epidemiological surveillance methods might further help shed light on how environmental factors impact NCDs, thereby offering more effective public health strategies (Raymos, 2023).



**Figure 1:** This flowchart illustrating the process of integrating Wastewater-Based Epidemiology (WBE) with predictive analytics for public health surveillance.

In fact, the scope of WBE informing public health policy is enormous in resource-limited settings where other traditional surveillance systems are inadequate. WBE will inform resource-allocation strategies and intervention strategies with real-time data about community health regarding diseases that have an environmental or lifestyle influence factor (Raymos, 2023; Matra, 2024). As such, tracing the progression of diseases within populations can inform public health administrators as to how interventions work and in which areas modifications are needed. The implementation of WBE for NCD monitoring still faces operational challenges, such as the need for strong quality assurance protocols and standardized methodologies (Gazeley, 2024).

## **2. Non-Communicable Diseases (NCDs) and Urban Health**

NCDs lead to approximately 38 million deaths annually, resulting in 35.6% of all adult deaths aged under 70, with a grossly disproportionate effect on LMICs (Musicha et al., 2016; Amara & Aljunid, 2014). Rapid urbanization in urban regions further exacerbates the prevalence of NCDs, which typically results in unhealthy lifestyles, including inadequate diets, a sedentary lifestyle, increased tobacco and alcohol use. For example, a study conducted in Accra, Ghana observed that high blood pressure and CVDs are the major contributors of one-third of NCDs burden that weighs heavily in urban prevalence, which is at 32.3% hypertension compared to rural prevalence that is only at 27% (Aikins et al., 2014). This imbalance among the urban and rural areas can be witnessed in other countries also, whereby the population dwelling in cities has a higher incidence rate of obesity, diabetes, and other risk factors prevalent (Supakul et al., 2019; Nawamawat et al., 2020).

Geographical variations also occur in NCDs' burden. For example, in the Middle East, the prevalence of NCDs is at 9%-50% in urban refugees. The most common conditions include musculoskeletal diseases, CVDs, and diabetes (Amara & Aljunid, 2014). On the other hand, Myanmar is one of those urban populations in Southeast Asia which trends concerning increased NCD risk factors such as higher cholesterol and prevalence of diabetes despite having a lower smoking rate compared to the rural population (Htet et al., 2016). This trend can be said to be in agreement with studies because lifestyle changes and environmental factors caused by urbanization have been noted to influence the risk for NCDs (Juma et al., 2020; Omotayo, 2024). Socio-economic factors also contribute to NCD burden in urbanized populations. Epidemics often have different characteristics among the rich and the poor population groups in sub-Saharan Africa, and thus have distinct profiles; in this regard, poor people face a dual burden of communicable and non-communicable diseases (Dagadu & Patterson, 2015). This is worsened by the fact that unplanned urban settlements have been linked to enhanced inequality, social deprivation, and access to health care services (Juma et al., 2020).

The economic burden of NCDs is high and cuts across countries in both the developed and developing world. The growing burden of NCDs is most likely to pose further pressures on already stretched health services, especially in LMICs, with significant unmet needs. Demographic shifts, aging populations, and continued lifestyles will continue to fuel the burden of NCDs, which is likely to increase, especially in urban settings (Jayaram et al., 2023; Omotayo, 2024). Major lifestyle modifications are part and parcel of the urban process: sedentary lifestyle, unwholesome dietary practices, and environmental pollutant exposure—all of these have given rise to NCDs, including cardiovascular diseases, diabetes, and chronic respiratory diseases. For NCDs, better surveillance systems are required especially since populations are growing in the urban settings (Sornpaisarn et al., 2023; Chauhan et al., 2022).

One of the main reasons for requiring new surveillance methods is that the existing data collection systems are inadequate. Traditional health surveillance relies on facility-based reporting, which does not take into account all NCD cases, especially the marginalized populations who often lack access to healthcare (Mocumbi et al., 2019; Kroll et al., 2015). For instance, facility-based surveillance systems in most low- and middle-income countries are usually under-resourced. The prevalence of NCDs is, therefore, underestimated since the majority of persons who do not seek medical care are not accounted for (Mocumbi

et al., 2019). Innovative methods, a community-based survey, and usage of technology have improved comprehensive surveillance of NCDs through their increased reach of the unreached population so that this produces a much clearer estimate of the burdened disease to be confronted Kroll et al., 2015; Kroll et al. 2016.

The COVID-19 pandemic has thus exposed the inadequacies that exist in any current NCD surveillance system: movement restrictions, as well as disruptions to the health services in place, prevent routine monitoring and management of the NCD (Chandran et al., 2021). Patients with NCDs are at higher risk of deteriorating outcomes in the wake of COVID-19; thus, alternative surveillance strategies that would ensure continued management and monitoring even during public health emergencies are critically needed (Chandran et al., 2021). New technologies, for example, telehealth and mobile health applications can easily monitor and treat NCDs in a crisis as well; therefore, improve the health condition of patients staying in an urban location (Sornpaisarn et al., 2023; Chandran et al., 2021).

Other factors why surveillance on NCD requires new ways is because the treatments on the same disease cost too much money. Urban health systems of many areas, especially low resource settings, lack the sufficient budgets to run wide-ranging surveillance activities (Sornpaisarn et al., 2023). Urban health authorities can scale up their capacity without having expensive cost by resorting to appropriate, cost-effective methods. A cost-effective way could be engaging already available community health workers or to integrate the surveillance of NCDs within primary healthcare, utilizing digital health technologies (Mocumbi et al., 2019; Sornpaisarn et al., 2023). This is an important issue in the urban setting where the burden of NCDs is usually accompanied by socio-economic disparities, thus requiring that the resources available be channeled effectively and appropriately (Haregu et al., 2015; Chauhan et al., 2022). In addition, relating to varieties of population and health-related issues and risky factors, surveillance methods need to be tailored according to specific community contexts (Haregu et al., 2015; Chauhan et al., 2022). Such tailored and innovative surveillance methods with local knowledge and community participation will enhance the applicability and reliability of the data gathered to ultimately improve the public health intervention (Sharma et al., 2021). For example, community member involvement in collecting and analyzing the data will allow for better insight into NCD risk factors at the local level and design appropriate interventions that take into account local culture (Sharma et al., 2021; Haregu et al., 2015).

### **3. Biomarkers of NCDs in Wastewater**

Wastewater-based epidemiology has been developed as a surveillance tool for public health and this is mainly through the study of various biomarkers found in wastewater. Biomarkers are trace substances that reflect the presence of a disease or health disorder. Normally, biomarkers include substances resulting from human metabolic activity. Some of the major categories of biomarkers used in WBE for NCD detection include metabolites associated with substance use, such as nicotine and its metabolite cotinine. These biomarkers would indicate tobacco consumption within a community, and thus provide useful information on the prevalence and time trends of smoking (Castiglioni et al., 2014). Another critical issue is that they should not degrade when they are transported with wastewater but should be detectable from the excretion point to the sampling site. It has been shown that quantification of the levels of nicotine and cotinine in wastewater acts as an indicator of smoking community rates and becomes a tool of public health (Castiglioni et al., 2014; Baz-Lomba et al., 2016).

In addition to tobacco-related biomarkers, WBE has been used for the monitoring of other substances that can potentially be used to affect NCD risk factors. For instance, alcohol metabolites in wastewater can be considered as a surrogate measure of patterns of alcohol consumption within the population (Baz-Lomba et al., 2016). This would give some impression of the nutritional status and lifestyles of populations if particular fatty acids and other metabolites that mark dietary intake were analyzed (Wu, 2023). The identified biomarkers might help point to communities that are at a risk of obesity and other NCDs, in which case, interventions through public health might be focused in such communities (Wu, 2023). It has also

been applied to study lifestyle factors like obesity and body activity because potential microbial biomarkers for community health are considered important. Wastewater microbiomes have been known to be correlated with lifestyle characteristics (Wu, 2023).

In the past few years have seen the application of WBE in monitoring residues of pharmaceuticals and their implications to the spread of chronic diseases, such as diabetes and hypertension. The use of antihypertensive and antidiabetic drugs in sewage can thus be regarded as a reflection of the disease burden in a community (Bade, 2023; Zhang et al., 2021). This approach can be utilized for the estimation of disease prevalence with minimal dependence on clinical data that may not be available in many populations (Zhang et al., 2021). As even the application of molecular techniques intermingles with wastewater analysis, the biomarkers associated with such diseases may find themselves potentially unmasked. That now enables making use of precise DNA biosensors for identification toward specific genetic conditions associated with unfavourable states of health amongst humans. A major area under one umbrella is, in fact, a more detailed approach toward an idea and its state that would offer understanding pertaining to health, Yang et al. (2015). This innovative approach increases the sensitivity and specificity of wastewater biomarker detection, thus better assessing community health (Yang et al., 2015).

Firstly, it has to do with basic inbuilt complexity relating to wastewater matrices. Wastewater comprises a colloidal suspension or heterogeneous mixture of organic and inorganic compounds, with suspended solids, pathogens, pharmaceuticals, and personal care items Coxon (2024) Sims et al., 2019). A complex can even decrease the specificity and sensitivity needed in analytical detection and quantification for individual biomarkers, otherwise; competing analytes diminish the analytical sensitivity and specificity Sims et al., 2019. For example, the presence of high concentrations of organic matter introduces matrix effects in complicating the interpretation, which makes difficult to accurately measure the biomarkers of interest; hence, (Sims et al., 2019; Hernández et al., 2016). The other difficulty in biomarkers detection is dynamic urban wastewater systems.

The sewer system of a city is in a constant change in terms of flow rates, and HRTs vary that may influence stability and concentration biomarkers while travelling through the network of the sewer system (Li et al., 2020). For example, several of the markers may degrade or alter during transportation. Such degradation or alteration might downsize the quantitative determination of such concentrations in waste water samples. This variation also demands developing the sampling protocol along with the corresponding analytical technique. It has the capability to correct for the described variations in biomarkers concentrations across the water way to produce consistent outcomes (Li et al., 2020; Alvi, 2024). In addition, the removal efficiency of wastewater treatment processes may directly influence the detectability of biomarkers. Most WWTPs conventional systems are designed to remove most contaminant types from wastewater, such as specific types of biomarkers associated with NCDs, not all contaminants (Kargar et al., 2013). Treatments have only been able to remove fractions of some of the biomarkers, hence their presence was evidenced in treated effluent (Kargar et al., 2013). Further, partial removal of these biomarkers makes interpretation of the biomarkers concentrations very complicated, which might confuse the residual contaminant that still remains with a product of treatment processes at community level (Kargar et al., 2013; Lopardo et al., 2017). The techniques in the analysis process for biomarker detection are a challenge.

Advanced techniques such as liquid chromatography-tandem mass spectrometry (LC-MS/MS) are most often necessary to be sensitive and specific for the detection of very low concentrations of biomarkers in the complex wastewater samples (Hernández et al., 2016; Ort et al., 2018). However, this application necessitates high-end instrumentation that requires highly trained personnel for its operation, making it out of reach and very difficult to be performed in resource-poor environments (Hernández et al., 2016). Moreover, the development and validation of novel analytical techniques for new emerging biomarkers may take a lot of time and may be costly, and therefore might slow WBE initiatives (Hernández et al., 2016; Ort et al., 2018). Public health in the interpretation of biomarker data becomes inherently complex. Biomarkers reflect individual health behaviors, but also a host of other environmental and social

determinants of health, as pointed out by Lopardo et al. (2017). Such changes in the concentration of biomarkers may therefore be affected by factors such as socioeconomic status, urban infrastructure, and healthcare services, among others, complicating the effort to associate observed trends with certain health outcomes, as highlighted by Lopardo et al. (2017).

#### **4. Predictive Analytics in Public Health**

Probably the most vital application of predictive analytics in public health is for outbreak prediction and management. As an example, predictive models have been developed for the prediction of the spread of infectious diseases such as influenza and COVID-19. Various sources of data are used for the same purpose. For example, the historical case counts, environmental determinants, and social determinants of health are considered Shah et al. (2018) Ebulue, (2024). These models may give a heads-up on potential future outbreaks so that public health authorities can readjust their resources appropriately and intervene at the right time (Ebulue, 2024). For instance, the use of VAR models to predict caseloads of COVID-19 is more accurate than the traditional epidemiological models (Shang et al., 2021).

Predictive analytics has also been applied to improve patient care and outcomes. Access to data by healthcare providers from electronic health records can help them identify high-risk readmission or complications, thereby allowing for targeted interventions that can reduce healthcare costs and improve patient outcomes (Kosaraju, 2024). Predictive models can look at the patterns of patient data and design treatment plans based on their needs. This leads to customized healthcare, where the outcome of this is raising the levels of satisfaction for patients and improving the health system (Kosaraju, 2024). Besides managing infectious diseases, predictive analytics has been applied in monitoring and managing chronic diseases. Data on lifestyle factors, medication adherence, and patient demographics analyzed will help health care providers understand trends and risk factors associated with hypertension, diabetes, and other conditions (Nor et al., 2020). Such information can be used in public health campaigns to promote healthier behaviors and improve disease management strategies within communities.

It helps in better decision-making by using predictive analytics in public health. In a traditional public health system, the decisions are mainly taken on basis of outdated information and subjective evaluations. This is less efficient and might also be prone to failure by missing the crucial window of intervention ("Integrating Data Analytics and Decision Support Systems in Public Health Management", 2024). It will make data-driven decisions that maybe timely and more responsive to new needs and health-related threats possible by using real-time and predictive models, hence asserts (Integrating Data Analytics and Decision Support Systems in Public Health Management", 2024). As things stand today, these systems are facing innumerable challenges as well as this transition towards data-based decision making becomes nearly indispensable for the public health.

However, with the full potential of predictive analytics in public health comes several challenges that need to be addressed. Data privacy issues, ethical considerations, and the need for robust infrastructure for data are the cornerstones of responsible use of predictive models (Molldrem et al., 2022). The quality of good and complete data used in the models is what dictates the accuracy and reliability of the models, hence the need to strive for constant improvement in data collection and integration in all sectors in public health (Zhang, 2023).

#### **5. Integration of WBE and Predictive Analytics**

Integration of WBE with predictive analytics promises to be the beacon for improvement in surveillance and response activities related to public health, especially infectious disease monitoring activities. Multiple frameworks and methodologies have been submitted for accomplishing such integration, taking advantage of relative strengths in WBE and predictive analytics in delivering real-time actionable insights into community health trends. Interestingly, Dai et al. proposed a Bayesian framework for modeling case numbers of COVID-19 by tracking SARS-CoV-2 RNA in wastewater with longitudinal monitoring. The

framework integrated clinical observations with wastewater surveillance data into a single cohesive predictive model based on functional principal component analysis (FPCA). The Bayesian framework addresses the challenges of sparse and noisy wastewater observations, enabling missing data to be imputed and the smoothing of signal functions, so that predictions with respect to trends in COVID-19 cases would be more accurate Dai 2024. This methodology shows how advanced statistical techniques can improve the reliability of WBE data in predicting incidence of disease.

Other important contributions carried out in this direction of WBE integration with predictive analytics come from Joseph-Duran et al. The study measures the potential of WBE to predict the cases of SARS-CoV-2 incidence in Catalonia, showing how real-time monitoring and extensive analysis of wastewater data presents relevance to prove the potential of the epidemiological surveillance that WBE might offer. Joseph-Duran et al. gives evidence of the usage of WBE in early warning systems for public health risks in associating wastewater data with clinical case counts. It can serve as a supplement while providing a replacement for traditional surveillance methods for a more integrated approach to community health dynamics (2022). Nourbakhsh et al. has developed a wastewater-based epidemic model targeting the SARS-CoV-2. This integrates the concentrations from wastewater, demographical data and clinical case data of three Canadian cities in order to construct a holistic view about the dynamics of the spread. The authors emphasize this calls for enough quantitative tools for this strength as well to translate what data are in the wastewater and translated to actionable public health measures through that while also filling out a large gap that would exist if using epidemiologic frameworks that were already established by others into some models; and such is giving examples in regards to adding further strength in capabilities from data integration or source (Nourbakhsh et al., 2022).

This study, Schill et al., explores the spatiotemporal relationship between COVID-19 cases and SARS-CoV-2 concentrations in wastewater. The authors also suggest supplementary data types-for example, hospitalization rates and vaccination status-become part of predictive models, so their outputs are realistic and meaningful. It suggests wastewater data-clinical outcomes modeling at a more contextual level in a bid to furnish enough periods of training so as to allow extracting meaningful training datasets from them by predictive models (Schill et al., 2023). This approach is incessantly reiterating that the contextualizing in wider epidemiological frames actually proves the requirement toward better use of contextualized WBE for improved predictiveness in analyses. On the other hand, Giglio et al. suggested that untreated wastewater can be used to track the trends of COVID-19. Their study reveals that the appearance of SARS-CoV-2 in wastewater can also serve as a predictor of clinical case trends and, therefore, strengthens the role of WBE as a non-invasive early alert for the monitoring of infectious disease outbreaks (Giglio et al., 2021).

A systematic review and meta-analysis of one major study done by Li et al demonstrated the association of SARS-CoV-2 RNA concentrations in wastewater with the number of cases of COVID-19 in the community. It showed that WBE could indeed capture the actual infection rates within communities as it captures the RNA from both symptomatic and asymptomatic patients, thus better representing the community's health Li et al. (2023). The study highlights how WBE may be used as a robust and reliable public health surveillance tool for communities with very few clinical testings. More validation evidence from Murakami about WBE is presented by an investigation to see how well survey techniques can assess the incidence of COVID-19. It showed that strong correlations are the SARS-CoV-2 RNA concentrations in wastewater and the confirmed cases of COVID-19 with respective correlation coefficient at  $r = 0.87$  for comprehensive notifiable disease surveillance and  $r = 0.86$  for sentinel surveillance (Murakami, 2024).

Furthermore, Arts et al. published on the longitudinal dynamics of SARS-CoV-2 and other viruses excreted in the stool that were normalized against markers for fecal strength, such as pepper mild mottle virus (PMMoV) and crAssphage (Arts et al., 2023). Normalization aids in improving the resolution of WBE data so that better estimation of viral load in wastewater and their implications on public health can be made.



This study indicates how fecal biomarkers can be used to enhance the accuracy of WBE in predicting the disease trend. Another such effort by Fitzgerald et al. in proving the workability of WBE is seen in their findings of site-specific correlations between SARS-CoV-2 viral loads and COVID-19 cases in influent wastewater treatment plants. They correlated wastewater measurements and reported COVID-19 incidence rates over the U.S., Australia, France, and Spain and had good correlation between both (Fitzgerald et al., 2021). This exemplifies how WBE can be used as a surveillance tool in the national domain to monitor the trends of a disease in multiple populations.

More than this, a study by Li et al. provided that WBE can predict new admissions to hospitals due to COVID-19 weekly more than 150 counties in the USA. Traditional record-based models were overtaken by this WBE predictive model that won an NMAE of 0.32–0.37 and leads the prediction as long as up to four weeks ago (Li et al., 2023). This is important because it will highlight the ability of WBE to provide timely insights into healthcare demands, which is crucial for resource allocation during public health emergencies. Wolfe et al. added strength to the data by studying the scaling of SARS-CoV-2 RNA in settled solids from several different wastewater treatment plants. Further on, their research supported the association of measurements in wastewater with the incidence rates of COVID-19, which aided in establishing more validity for WBE as a surveillance tool (Wolfe et al., 2021). Therefore, their conclusion shows the possibility of using WBE for early warning systems and monitoring disease trends in urban population groups. Finally, Fernández-Cassi et al. reported that monitoring of wastewater might be even more sensitive than the case numbers for tracking the dynamics of COVID-19 incidence, especially at a high test positivity rate. In fact, their research showed that WBE might have the potential to capture the introduction and spread of SARS-CoV-2 variants, thus providing important information not possibly obtained from clinical testing alone (Fernández-Cassi et al., 2021).

## 6. Challenges and Gaps in Current Literature

This can create one of the major inconsistencies when dealing with the high day-to-day variability in wastewater data, especially in smaller communities or low-incidence situations. Nauta et al. note that such variability can make the interpretation of wastewater surveillance data difficult, thereby drawing unreliable conclusions regarding local outbreaks Nauta et al. (2023). For instance, the probability of detection of viral RNA in wastewater can be low, and the chance of underreporting community transmission might be high in the case where a few people are shedding the virus in a large population. Variability requires robust statistical approaches to manage fluctuations and make more accurate predictions. Another incompatibility issue deals with the degradation of RNA of samples collected from wastewater. This factor affects the quality and reliability of data gathered. Baaijens et al. note that the problem of RNA degradation is what fails the sequencing techniques deployed for analyzing viral content in wastewater (Baaijens et al., 2022). The degradation of short RNA fragments might not be suitable to high-throughput long-read sequencing, hence limiting the ability to acquire accurate quantification of viral lineages and prevalence in the community. This results in fragmented assemblies that do not represent the viral population, hence making it difficult to interpret the results.

Besides, the methodologies adopted in WBE are quite diverse in different studies, which has resulted in the inconsistency of data collection and analysis. For instance, while some use linear regression or nonlinear regression models to predict the incidence of diseases based on wastewater data, others use more complex Bayesian frameworks (Dai, 2024). The lack of standardization in analytical techniques results in disparate findings and complicates the comparison of results across studies. This inconsistency calls for a standardized methodological approach to increase the reliability of WBE data and its integration with predictive analytics. Data sharing and collaboration are further challenges of inconsistencies in WBE methodologies. According to Naughton et al., more data sharing can lead to comparative analysis across different collection sites, which will enable the identification of effective methods in various settings (Naughton et al., 2021). Nevertheless, such discrepancies would reduce the processability and introduce possible biases or inaccuracies in the data interpretation of WBE. Such factors may particularly be

important in low-resource settings where the resources for aggressively collecting data and analyzing it might be limited.

Finally, the reliance of predictive analytics on assumptions of how wastewater data relates to case counts at the clinics further clouds the effectiveness of the methods. According to Nemudryi et al., despite the capacity of WBE prevalence estimation to incorporate input from the whole community, its prevalence estimate remains sensitive to many assumptions and conditions such as viral load in stool, degradation rates, and water use per capita (Nemudryi et al., 2020). Therefore, such assumptions might lead to uncertainties when using the predictions generated through such models. Additionally, it has the scope for bias in sampling techniques that may cause disparity in WBE data. Moreover, it is also of significant importance in sewer connectivity along with its significance to equity issues in wastewater surveillance as mentioned in Yu et al., 2023.

It presents a good number of ethical issues that need reflection to ensure responsible execution and trust by the public when using WBE in public health surveillance for monitoring matters. These concerns are basically outlined around the aspects of privacy, consent, data interpretation, and informational misuse. The most associated ethical issue related to WBE is privacy. Wastewater contains a rich bio-material from all walks of life, and testing this bio-material might reveal health status and habits in the community. According to Kannan et al., collection and assessment of such water data should be done in an open manner without trespassing on the privacy rights of individuals Kannan et al. (2022). This means that while identifying specific diseases or specific behavior through analysis of wastewaters questions arise in terms of information to public sources and which kind of measures this may take against the general population by any concerned authority.

Apart from privateness and confidence issues another fundamental problem relevant for WBE lies in consensus. Unlike conventional public health surveillance approaches, which require informed consent from participants, WBE is based on the analysis of community wastewater without individual consent. Lajoie et al. discuss the subtleties of this ethical dilemma: while people may not have given any consent to allow the analysis of their wastewater, they are, in fact contributing to the collected data (LaJoie et al., 2023). Ethical responsibility occurs here in that data so used for public health surveillance should not leak out the community, which should be informed of the possibility of their wastewater to be analyzed.

Data interpretation and the possibility of findings being misrepresented also raise ethical issues. The methodologies of WBE may vary significantly, leading to conflicting data quality and interpretation. Hrudehy et al. have stressed the need for ethical considerations in interpreting wastewater data to avoid coming to misleading conclusions that may influence public health responses (Hrudehy et al., 2021). There is likely to be some misinterpretation of data that could lead to undue panic or complacency within communities, hence careful communication of findings is important. This also raises ethical concerns in that information derived from WBE may be used in ways detrimental to public health. For instance, applying the data on wastewater to enforcement actions or public health interventions on defined populations can stigmatize or discriminate against the defined populations. Mills acknowledges that WBE is a very crucial source of information on health in the community but argues that much attention needs to be paid to the application of the information and its implications to individuals and communities (Mills, 2023). Ethical frameworks have to be drawn for guiding the responsible use of WBE data, avoiding harm, and ascertaining equitable practices of public health.

Other ethical issues concerning WBE are community engagement and public discussion. According to Amman et al., WBE implementation should present an opportunity to involve community people in discussion to overcome their fears and discuss with them to gain their trust over the surveillance system (Amman et al., 2022). The public discussion over the advantages and disadvantages of WBE may help in

alleviating people's fear towards it and increase public awareness about health policies. Lastly, there is a possibility of WBE worsening the already debilitating health disparities. According to Rosa et al., while WBE can help in providing useful data for public health surveillance, it is important that the benefits of such technology be equitably distributed within different communities (Rosa et al., 2020).

## 7. Emerging Trends and Future Perspectives

**Table 1: Advancements in Wastewater-Based Monitoring and Their Applications to Public Health.**

Advancement	Description	Reference
Enhanced Detection Methods	Advanced molecular techniques, such as metatranscriptomics and nanopore sequencing, enable precise pathogen and biomarker identification, aiding biosurveillance of diseases.	Spurbeck et al. (2023)
Integration of Genomic Analysis	Genomic analysis of wastewater provides insights into pathogen diversity and genetic markers of diseases, helping identify unreported outbreaks and track NCDs.	Diemert & Yan (2019)
Correlation with Health Outcomes	Linking wastewater data with health outcomes allows researchers to establish connections between biomarkers and disease prevalence, informing public health strategies.	Huang et al. (2022)
Real-Time Monitoring	Remote sensing technology and real-time data analysis enable continuous monitoring of wastewater systems, offering early warnings for health risks.	"Early Warning System..." (2023)
Improved Treatment Technologies	Advanced treatment technologies like CEPT and AOPs enhance wastewater quality, improving the accuracy of analyses for NCD-related biomarkers.	Shewa & Dagne (2020)

Data Standardization and Methodology	Standardized protocols for sample collection, processing, and analysis improve the reliability and comparability of wastewater data.	Huang et al. (2022)
Community Engagement and Acceptance	Community involvement ensures public understanding and acceptance of wastewater analysis methods, crucial for successful implementation.	Singha & Eljamal (2022)

The integration of wastewater-based epidemiology (WBE) with predictive analytics presents a unique opportunity to enhance public health surveillance, particularly in urban populations. However, to ensure that this integration provides equitable health benefits for all urban communities, several strategies must be implemented. These strategies focus on addressing health disparities, fostering community engagement, and ensuring that technological advancements are accessible to all populations.

**Table 2: Strategies for Promoting Health Equity through Wastewater-Based Epidemiology (WBE).**

Strategy	Description	Reference
<b>Addressing Health Disparities</b>	Urban governance and planning can target social determinants of health, incorporating WBE into strategies to prioritize disadvantaged communities' needs.	Makadzange et al. (2018)
<b>Community Engagement and Empowerment</b>	Engaging communities in WBE design fosters trust and ensures data relevance, through consultations, educational campaigns, and partnerships with local groups.	Corburn (2017)
<b>Oversampling Underserved Populations</b>	Intentional oversampling ensures representation of underserved communities, enabling accurate health assessments and tailored interventions.	Smith et al. (2022)

<b>Standardization of Methodologies</b>	Establishing standardized protocols for sampling and analysis enhances data comparability and reliability across urban settings.	Bowes (2024)
<b>Leveraging Technological Advancements</b>	Advanced technologies like next-generation sequencing improve sensitivity for detecting NCD-related biomarkers and informing timely interventions.	Michie (2024)
<b>Policy Recommendations and Advocacy</b>	WBE data can inform equitable policies addressing health disparities and promote access to healthcare for marginalized populations.	Amri et al. (2022)
<b>Intersectoral Collaboration</b>	Collaboration across sectors (public health, urban planning, environmental management) enables comprehensive strategies using WBE data.	Serrano et al. (2016)

## Conclusion

WBE and predictive analytics integration into surveillance is a paradigm shift with unprecedented opportunities in real-time monitoring of NCD in urban populations. WBE enables the capture of community health dynamics through biomarkers, and PA can forecast long-term trends hence providing a rich framework for the proactive interventions required in public health. This approach addresses shortcomings of traditional surveillance systems by provision of cost-effective, non-invasive, and comprehensive health data. Applications include infectious diseases only, as it can be utilized to track biomarkers of NCDs that include diabetes, cardiovascular diseases, and obesity among others. Integration supports tailored public health strategies addressing socio-economic disparities in urban health. Significant challenges persist, which include the necessity for standardized methodologies, robust frameworks in place to protect data, and considerations about ethics and preventing misuse. The variability in wastewater data together with the intricacies of the urban sewage systems demands advanced techniques in analysis as well as transdisciplinary collaboration. Engaging the communities in designing and implementing the WBE system is also an essential requirement in gaining public trust and acceptance. It does face various challenges, yet in unison with predictive analytics and WBE, public health has every chance to get transformed to help with interventions and allocation of the resource. Since urban population keeps growing, a solution of integrating the WBE and PA system could become quite scalable and sustainable to counter this growing NCD burden.

## Conflict of Interest

The authors declare they don't have any conflict of interest.

### Author contributions

The first drafts of the work is written by the first author and the cross-ponding author's supervisor it. Each author wrote a portion of the manuscript, collected data, edited it, created tables, and got permission to submit it to a journal for publication.

### Acknowledgement

The authors thank numerous resources for offering open access publications, including Google Scholar, DOAJ, Research Gate, Embase, PubMed, Cochrane Library, Web of Science, BMJ Clinical Evidence, and Medline.

### Ethical Approval

Not Applicable

---

### References

1. Aikins, A., Kushitor, M., Koram, K., Gyamfi, S., & Ogedegbe, G. (2014). Chronic non-communicable diseases and the challenge of universal health coverage: insights from community-based cardiovascular disease research in urban poor communities in accra, ghana. *BMC Public Health*, 14(S2). <https://doi.org/10.1186/1471-2458-14-s2-s3>
2. Agrawal, S., Orschler, L., Schubert, S., Zachmann, K., Heijnen, L., Tavazzi, S., ... & Lackner, S. (2021). A pan-european study of sars-cov-2 variants in wastewater under the eu sewage sentinel system.. <https://doi.org/10.1101/2021.06.11.21258756>
3. Alvi, M. (2024). Automated state estimation for summarizing the dynamics of complex urban systems using representation learning. *Proceedings of the Aaai Conference on Artificial Intelligence*, 38(21), 23020-23026. <https://doi.org/10.1609/aaai.v38i21.30344>
4. Amara, A. and Aljunid, S. (2014). Noncommunicable diseases among urban refugees and asylum-seekers in developing countries: a neglected health care need. *Globalization and Health*, 10(1), 24. <https://doi.org/10.1186/1744-8603-10-24>
5. Amman, F., Markt, R., Endler, L., Hupfau, S., Agerer, B., Schedl, A., ... & Bergthaler, A. (2022). Viral variant-resolved wastewater surveillance of sars-cov-2 at national scale. *Nature Biotechnology*, 40(12), 1814-1822. <https://doi.org/10.1038/s41587-022-01387-y>
6. Amri, M., O'Campo, P., Enright, T., Siddiqi, A., Ruggiero, E., & Bump, J. (2022). Probing key informants' views of health equity within the world health organization's urban heart initiative. *BMC Public Health*, 22(1). <https://doi.org/10.1186/s12889-022-14395-z>
7. Arts, P., Kelly, J., Midgley, C., Anglin, K., Lu, S., Abedi, G., ... & Wigginton, K. (2023). Longitudinal and quantitative fecal shedding dynamics of sars-cov-2, pepper mild mottle virus, and crassphage. *Msphere*, 8(4). <https://doi.org/10.1128/msphere.00132-23>
8. Baaijens, J., Zulli, A., Ott, I., Nika, I., Lugt, M., Petrone, M., ... & Baym, M. (2022). Lineage abundance estimation for sars-cov-2 in wastewater using transcriptome quantification techniques. *Genome Biology*, 23(1). <https://doi.org/10.1186/s13059-022-02805-9>
9. Bade, R. (2023). Improving wastewater-based epidemiology for new psychoactive substance surveillance by combining a high-throughput in vitro metabolism assay and lc-hrms metabolite identification.. <https://doi.org/10.26434/chemrxiv-2023-mvc6g>
10. Baz-Lomba, J., Salvatore, S., Gracia-Lor, E., Bade, R., Castiglioni, S., Castrignanò, E., ... & Thomas, K. (2016). Comparison of pharmaceutical, illicit drug, alcohol, nicotine and caffeine levels in wastewater with sale, seizure and consumption data for 8 european cities. *BMC Public Health*, 16(1). <https://doi.org/10.1186/s12889-016-3686-5>
11. Bowes, D. (2024). Wastewater-based epidemiology to assess environmentally influenced disease. *Journal of Exposure Science & Environmental Epidemiology*, 34(3), 387-388. <https://doi.org/10.1038/s41370-024-00683-w>

12. Castiglioni, S., Senta, I., Borsotti, A., Davoli, E., & Zuccato, E. (2014). A novel approach for monitoring tobacco use in local communities by wastewater analysis. *Tobacco Control*, 24(1), 38-42. <https://doi.org/10.1136/tobaccocontrol-2014-051553>
13. Chandran, A., Kumar, S., Hairi, N., Low, W., & Mustapha, F. (2021). Non-communicable disease surveillance in malaysia: an overview of existing systems and priorities going forward. *Frontiers in Public Health*, 9. <https://doi.org/10.3389/fpubh.2021.698741>
14. Chauhan, S., Kumar, S., Patel, R., Simon, D., & Kumari, A. (2022). Burden of communicable and non-communicable diseases-related inequalities among older adults in india: a study based on lasi survey. *BMC Geriatrics*, 22(1). <https://doi.org/10.1186/s12877-022-03481-x>
15. Corburn, J. (2017). Urban place and health equity: critical issues and practices. *International Journal of Environmental Research and Public Health*, 14(2), 117. <https://doi.org/10.3390/ijerph14020117>
16. Coxon, G. (2024). Wastewater discharges and urban land cover dominate urban hydrology signals across england and wales. *Environmental Research Letters*, 19(8), 084016. <https://doi.org/10.1088/1748-9326/ad5bf2>
17. Daughton, C. (2020). Wastewater surveillance for population-wide covid-19: the present and future. *The Science of the Total Environment*, 736, 139631. <https://doi.org/10.1016/j.scitotenv.2020.139631>
18. Dagadu, H. and Patterson, E. (2015). Placing a health equity lens on non-communicable diseases in sub-saharan africa. *Journal of Health Care for the Poor and Underserved*, 26(3), 967-989. <https://doi.org/10.1353/hpu.2015.0097>
19. Dai, X. (2024). A bayesian framework for modeling covid-19 case numbers through longitudinal monitoring of sars-cov-2 rna in wastewater. *Statistics in Medicine*, 43(6), 1153-1169. <https://doi.org/10.1002/sim.10009>
20. Diemert, S. and Yan, T. (2019). Clinically unreported salmonellosis outbreak detected via comparative genomic analysis of municipal wastewater salmonella isolates. *Applied and Environmental Microbiology*, 85(10). <https://doi.org/10.1128/aem.00139-19>
21. Ebulue, C. (2024). Environmental data in epidemic forecasting: insights from predictive analytics. *Computer Science & It Research Journal*, 5(5), 1113-1125. <https://doi.org/10.51594/csitrj.v5i5.1118>
22. Fernández-Cassi, X., Scheidegger, A., Bänziger, C., Cariti, F., Corzón, Á., Ganesanandamoorthy, P., ... & Kohn, T. (2021). Wastewater monitoring outperforms case numbers as a tool to track covid-19 incidence dynamics when test positivity rates are high. *Water Research*, 200, 117252. <https://doi.org/10.1016/j.watres.2021.117252>
23. Fontenele, R., Kraberger, S., Hadfield, J., Driver, E., Bowes, D., Holland, L., ... & Varsani, A. (2021). High-throughput sequencing of sars-cov-2 in wastewater provides insights into circulating variants.. <https://doi.org/10.1101/2021.01.22.21250320>
24. Fitzgerald, S., Rossi, G., Low, A., McAteer, S., O'Keefe, B., Findlay, D., ... & Corbishley, A. (2021). Site specific relationships between covid-19 cases and sars-cov-2 viral load in wastewater treatment plant influent. *Environmental Science & Technology*, 55(22), 15276-15286. <https://doi.org/10.1021/acs.est.1c05029>
25. Gazeley, J. (2024). Correlating quantitative and genomic sars-cov-2 wastewater data with clinical metrics in metropolitan perth, western australia. *Environments*, 11(4), 62. <https://doi.org/10.3390/environments11040062>
26. Giglio, O., Triggiano, F., Apollonio, F., Diella, G., Fasano, F., Stefanizzi, P., ... & Montagna, M. (2021). Potential use of untreated wastewater for assessing covid-19 trends in southern italy. *International Journal of Environmental Research and Public Health*, 18(19), 10278. <https://doi.org/10.3390/ijerph181910278>
27. Haregu, T., Oti, S., Egondi, T., & Kyobutungi, C. (2015). Co-occurrence of behavioral risk factors of common non-communicable diseases among urban slum dwellers in nairobi, kenya. *Global Health Action*, 8(1), 28697. <https://doi.org/10.3402/gha.v8.28697>
28. Hernández, F., Castiglioni, S., Covaci, A., Voogt, P., Emke, E., Kasprzyk-Hordern, B., ... & Bijlsma, L. (2016). Mass spectrometric strategies for the investigation of biomarkers of illicit drug use in wastewater. *Mass Spectrometry Reviews*, 37(3), 258-280. <https://doi.org/10.1002/mas.21525>

29. Hrudehy, S., Silva, D., Shelley, J., Pons, W., Isaac-Renton, J., Chik, A., ... & Conant, B. (2021). Ethics guidance for environmental scientists engaged in surveillance of wastewater for sars-cov-2. *Environmental Science & Technology*, 55(13), 8484-8491. <https://doi.org/10.1021/acs.est.1c00308>
30. Htet, A., Bjertness, M., Sherpa, L., Kjøllesdal, M., Oo, W., Meyer, H., ... & Bjertness, E. (2016). Urban-rural differences in the prevalence of non-communicable diseases risk factors among 25–74 years old citizens in yangon region, myanmar: a cross sectional study. *BMC Public Health*, 16(1). <https://doi.org/10.1186/s12889-016-3882-3>
31. Huang, Y., Zhou, N., Zhang, S., Yi, Y., Han, Y., Liu, M., ... & Jin, H. (2022). Norovirus detection in wastewater and its correlation with human gastroenteritis: a systematic review and meta-analysis. *Environmental Science and Pollution Research*, 29(16), 22829-22842. <https://doi.org/10.1007/s11356-021-18202-x>
32. Jayaram, K., Krishnasamy, V., & Jayaseelan, V. (2023). Protocol of randomized controlled trial to evaluate the effectiveness of nurse-led intervention on weight reduction among adults with obesity in urban areas of puducherry. *Indian Journal of Endocrinology and Metabolism*, 27(2), 154-160. [https://doi.org/10.4103/ijem.ijem\\_404\\_22](https://doi.org/10.4103/ijem.ijem_404_22)
33. Joseph-Duran, B., Serra-Compte, A., Sarrias, M., González, S., López, D., Prats, C., ... & Arnaldos, M. (2022). Assessing wastewater-based epidemiology for the prediction of sars-cov-2 incidence in catalonia. *Scientific Reports*, 12(1). <https://doi.org/10.1038/s41598-022-18518-9>
34. Juma, K., Juma, P., Shumba, C., Otieno, P., & Asiki, G. (2020). Non-communicable diseases and urbanization in african cities: a narrative review.. <https://doi.org/10.5772/intechopen.89507>
35. Kannan, V., Meganathan, S., & Mishra, R. (2022). Wastewater surveillance for public health: beyond the pandemic. *Journal of Science Policy & Governance*, 21(02). <https://doi.org/10.38126/jspg210207>
36. Kantor, R., Greenwald, H., Kennedy, L., Hinkle, A., Harris-Lovett, S., Metzger, M., ... & Nelson, K. (2022). Operationalizing a routine wastewater monitoring laboratory for sars-cov-2. *Plos Water*, 1(2), e0000007. <https://doi.org/10.1371/journal.pwat.0000007>
37. Kargar, M., Javdani, N., Najafi, A., & Tahamtan, Y. (2013). First molecular detection of group a rotavirus in urban and hospital sewage systems by nested-rt pcr in shiraz, iran. *Journal of Environmental Health Science and Engineering*, 11(1). <https://doi.org/10.1186/2052-336x-11-4>
38. Kosaraju, D. (2024). Predictive analytics in healthcare: leveraging ai to anticipate disease outbreaks and enhance patient outcomes. *Galore International Journal of Health Sciences and Research*, 8(3), 73-79. <https://doi.org/10.52403/gijhsr.20230312>
39. Kroll, M., Phalkey, R., & Kraas, F. (2015). Challenges to the surveillance of non-communicable diseases – a review of selected approaches. *BMC Public Health*, 15(1). <https://doi.org/10.1186/s12889-015-2570-z>
40. Kroll, M., Phalkey, R., Dutta, S., Shukla, S., Butsch, C., Bharucha, E., ... & Kraas, F. (2016). Involving private healthcare practitioners in an urban ncd sentinel surveillance system: lessons learned from pune, india. *Global Health Action*, 9(1), 32635. <https://doi.org/10.3402/gha.v9.32635>
41. Kumar, M., Patel, A., Shah, A., Raval, J., Rajpara, N., Joshi, M., ... & Joshi, C. (2020). First proof of the capability of wastewater surveillance for covid-19 in india through detection of genetic material of sars-cov-2. *The Science of the Total Environment*, 746, 141326. <https://doi.org/10.1016/j.scitotenv.2020.141326>
42. Li, J., Gao, J., Thai, P., Mueller, J., Yuan, Z., & Jiang, G. (2020). Transformation of illicit drugs and pharmaceuticals in sewer sediments. *Environmental Science & Technology*, 54(20), 13056-13065. <https://doi.org/10.1021/acs.est.0c04266>
43. Miyani, B., Fonoll, X., Norton, J., Mehrotra, A., & Xagorarakis, I. (2020). Sars-cov-2 in detroit wastewater. *Journal of Environmental Engineering*, 146(11). [https://doi.org/10.1061/\(asce\)ee.1943-7870.0001830](https://doi.org/10.1061/(asce)ee.1943-7870.0001830)
44. Rao, G. (2024). Simultaneous detection and quantification of multiple pathogen targets in wastewater. *Plos Water*, 3(2), e0000224. <https://doi.org/10.1371/journal.pwat.0000224>



45. Rousis, N., Gracia-Lor, E., Zuccato, E., Bade, R., Baz-Lomba, J., Castrignanò, E., ... & Castiglioni, S. (2017). Wastewater-based epidemiology to assess pan-european pesticide exposure. *Water Research*, 121, 270-279. <https://doi.org/10.1016/j.watres.2017.05.044>
46. LaJoie, A., Holm, R., Anderson, L., Ness, H., & Smith, T. (2023). Tracking national opinion about wastewater monitoring as a standard complement of public health tools in the united states.. <https://doi.org/10.1101/2023.06.16.23291485>
47. Li, X., Liu, H., Sherchan, S., Zhou, T., Khan, S., Loosdrecht, M., ... & Wang, Q. (2023). Wastewater-based epidemiology predicts covid-19-induced weekly new hospital admissions in over 150 usa counties. *Nature Communications*, 14(1). <https://doi.org/10.1038/s41467-023-40305-x>
48. Li, X., Zhang, S., Sherchan, S., Orive, G., Lertxundi, U., Haramoto, E., ... & Jiang, G. (2023). Correlation between sars-cov-2 rna concentration in wastewater and covid-19 cases in community: a systematic review and meta-analysis. *Journal of Hazardous Materials*, 441, 129848. <https://doi.org/10.1016/j.jhazmat.2022.129848>
49. Lopardo, L., Cummins, A., Rydevik, A., & Kasprzyk-Hordern, B. (2017). New analytical framework for verification of biomarkers of exposure to chemicals combining human biomonitoring and water fingerprinting. *Analytical Chemistry*, 89(13), 7232-7239. <https://doi.org/10.1021/acs.analchem.7b01527>
50. Makadzange, K., Radebe, Z., Maseko, N., Lukhele, V., Masuku, S., Fakudze, G., ... & Prasad, A. (2018). Implementation of urban health equity assessment and response tool: a case of matsapha, swaziland. *Journal of Urban Health*, 95(5), 672-681. <https://doi.org/10.1007/s11524-018-0241-y>
51. Mao, K., Zhang, K., Du, W., Ali, W., Feng, X., & Zhang, H. (2020). The potential of wastewater-based epidemiology as surveillance and early warning of infectious disease outbreaks. *Current Opinion in Environmental Science & Health*, 17, 1-7. <https://doi.org/10.1016/j.coesh.2020.04.006>
52. Matra, S. (2024). Wastewater surveillance of open drains for mapping the trajectory and succession of sars-cov-2 lineages in 23 class-i cities of maharashtra state (india) during june 2022 to may 2023.. <https://doi.org/10.21203/rs.3.rs-4609404/v1>
53. Michie, A. (2024). Wastewater-based sars-cov-2 surveillance and sequencing. *Microbiology Australia*, 45(1), 8-12. <https://doi.org/10.1071/ma24004>
54. Mills, C. (2023). Strategic use of sars-cov-2 wastewater concentration data could enhance, but not replace, high-resolution community prevalence survey programmes.. <https://doi.org/10.1101/2023.08.17.23293589>
55. Mocumbi, A., Langa, D., Chicumbe, S., Schumacher, A., & Al-Delaimy, W. (2019). Incorporating selected non-communicable diseases into facility-based surveillance systems from a resource-limited setting in africa. *BMC Public Health*, 19(1). <https://doi.org/10.1186/s12889-019-6473-2>
56. Molldrem, S., Smith, A., & McClelland, A. (2022). Predictive analytics in hiv surveillance require new approaches to data ethics, rights, and regulation in public health. *Critical Public Health*, 33(3), 275-281. <https://doi.org/10.1080/09581596.2022.2113035>
57. Murakami, M. (2024). Evaluating survey techniques in wastewater-based epidemiology for accurate covid-19 incidence estimation.. <https://doi.org/10.1101/2024.06.09.24308677>
58. Musicha, C., Crampin, A., Kayuni, N., Koole, O., Amberbir, A., Mwagomba, B., ... & Nyirenda, M. (2016). Accessing clinical services and retention in care following screening for hypertension and diabetes among malawian adults. *Journal of Hypertension*, 34(11), 2172-2179. <https://doi.org/10.1097/hjh.0000000000001070>
59. Naik, S. (2023). Wastewater surveillance for disease epidemiology. *Indian Public Policy Review*, 4(6 (Nov-Dec)), 45-65. <https://doi.org/10.55763/ippr.2023.04.06.003>
60. Naughton, C.,
61. Serrano, E., Larrañaga, I., Morteruel, M., Ros, M., Basterrechea, M., D, M., ... & Bacigalupe, A. (2016). Urban regeneration as population health intervention: a health impact assessment in the bay of pasaia (spain). *International Journal for Equity in Health*, 15(1). <https://doi.org/10.1186/s12939-016-0424-7>
62. Smith, T., Holm, R., Yeager, R., Moore, J., Rouchka, E., Sokoloski, K., ... & Bhatnagar, A. (2022). Combining community wastewater genomic surveillance with state clinical surveillance: a framework

- for sars-cov-2 public health practice. Food and Environmental Virology, 14(4), 410-416.  
<https://doi.org/10.1007/s12560-022-09531-2>
63. Shewa, W. and Dagnew, M. (2020). Revisiting chemically enhanced primary treatment of wastewater: a review. Sustainability, 12(15), 5928. <https://doi.org/10.3390/su12155928>
64. Singha, B. and Eljamal, O. (2022). Evaluating the social and psychological factors about the public acceptance of treated wastewater reuse: a review. Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (Ieices), 8, 234-238.  
<https://doi.org/10.5109/5909097>
65. Spurbeck, R., Catlin, L., Mukherjee, C., Smith, A., & Minard-Smith, A. (2023). Analysis of metatranscriptomic methods to enable wastewater-based biosurveillance of all infectious diseases. Frontiers in Public Health, 11. <https://doi.org/10.3389/fpubh.2023.1145275>