

# Urban Intelligence for Planetary Health

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**Abstract:** The health of human-being and our planet are incessantly interlinked, and such links often exist in the context of cities. This article articulates urban intelligence as an essential capacity for cities to be more adaptive and responsive to face the risks in the context of climate change and global pandemics. Urban intelligence includes data intelligence, design intelligence, and crowd intelligence, which collectively contribute to planetary health with better understandings in cities' complex physical-environmental-technical-social dynamics. In the long run, urban intelligence supports cities by enabling a better conceptual understanding of human-earth conflicts, transdisciplinary research in the science of the cities, and governmental collaborations at the local and global scale.

**Keywords:** urban intelligence; urban science; planetary health

## 1. Introduction

Planetary health is physical and environmental that cannot be solely addressed by information and computation, requires transdisciplinary approaches to bring people, places, and policy together with science and technology. The health of human-being and our planet are incessantly interlinked, and such links often exist in the context of cities. In December 2020, the total of human-made materials outweighed all living things on the planet for the first time, and most non-organic materials, including concrete, asphalt, and plastics, are produced, consumed, and wasted in cities [1]. With 55% of human beings settling in urbanized areas (and soon to be 68% by 2050), cities play a critical role in shaping earth systems and population health—eventually planetary health [2]. Meanwhile, new information technology and rapidly evolving social-technical complexities lead to urban science as an emerging field investigating urban problems and innovations [3].

Cities are critical for planetary health considering their characteristics, such as the typical urban setting (e.g., dense built environment, extensive spatial coverage, large population, intense energy consumption), complex challenges (e.g., climate change, natural disaster, population health, equity, and aging society), and opportunities (e.g., economic power, technological innovation, and political influence) [4]. Urban studies contribute transdisciplinary understandings in planetary health at the human scale, particularly in the context of climate change, natural disasters, and global pandemics [5]. Relevant studies include but are not limited to investigating the relationship between urban form and public health outcome [6], active mobility and mortality [7], the health impact of building efficiency [8], and air quality [9]. Although such studies contribute to a better understanding of cities, there are gaps between quantitative and qualitative approaches involving data science, policy analysis, urban design, and other aspects.

Urban intelligence is a capacity derived from the research and practice of urban science and related fields, representing a capacity to sense, observe, quantify, analyze, and manage complex urban systems and resultant dynamic behavior in cities [10]. Ideally, urban intelligence can connect quantitative and qualitative approaches, enabling integrated investigations and intervention of complex urban systems. However, it is not clear how this capacity may support cities to cope with planetary health-related issues. Therefore, this article aims to conceptualize major types of urban intelligence and their relevance to planetary health. The rest of this article proceeds as the following: The author first



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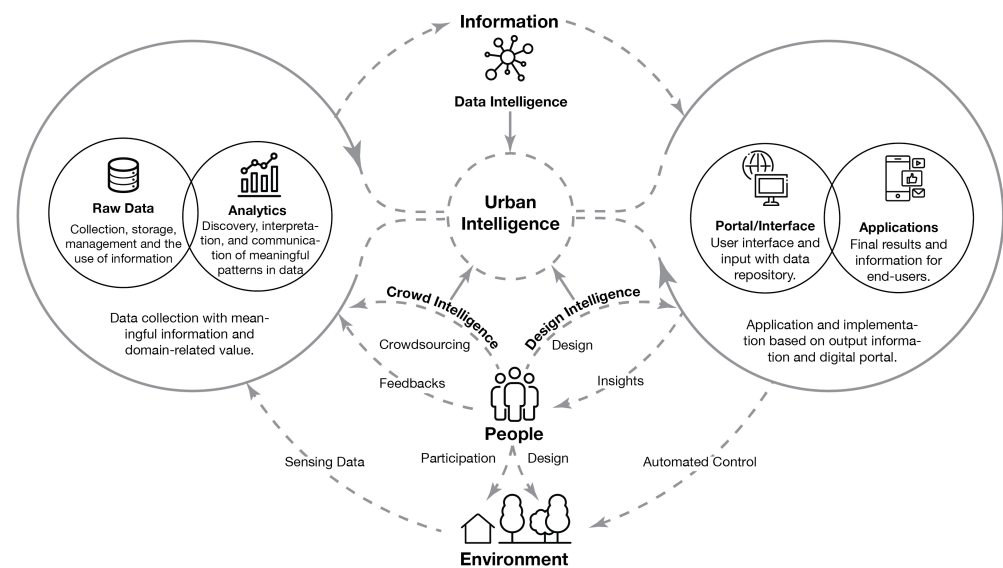
explains the origin, definition, and research paradigm of urban science and how urban intelligence derives from the research and practice of urban science. Then the author articulates three major types of urban intelligence—data intelligence, design intelligence, and crowd intelligence. The article further explains how urban intelligence plays a critical role in addressing planetary health. Finally, the discussion and conclusion summarize the current ongoing challenges for cities and how urban intelligence provides unique value for future planetary health.

## 2. Urban Science and Urban Intelligence

Historically, urban planners played an essential role in shaping modern cities with tremendous contributions and mistakes, causing segregation, discrimination, and injustice, especially in public health and access to opportunities. Urban Science is an emerging research field focusing on transdisciplinary investigations on the system configuration, design, behavior, and phenomena of cities [11]. Two branches of urban science originate from different philosophical views, representing “Science of Cities” and “Applied Urban Science” (or “Urban Informatics”) [12]. Science of Cities tends to treat cities as research objects by investigating the physical dynamics, geographical pattern, and spatial-temporal regularities. In contrast, applied urban science emphasizes integrating scientific research and technology implementations in the context of cities. While such two views project different questions, methods, and applications, the common ground is to utilize new data, analytics, and technology innovation to improve cities, ranging from micro-scale personal quality-of-life to meso- or macro-scale regional ecological, economic, and social development. In summary, urban science is a research field utilizing big data, analytics, and ubiquitous computing devices to gain more scientific understandings and technological interventions in increasingly complex cities.

Three major types of urban intelligence are data intelligence, design intelligence, and crowd intelligence. Figure 1 illustrates a conceptual framework of urban intelligence. Data intelligence relies on rich data resources, urban data science analytical capacity, and operational power. Many cities and agencies collect, store, manage diverse data, which data scientists can further analyze to construct statistical or machine learning models [13]. Data analytics can discover underlying patterns, interpret the results, and communicate with non-technical experts (usually, policymakers, investors, service operators) to further identify the value of data and gain insights from subject matter experts. This process also ensures that the findings or solutions derived from data-driven analytics can properly suit targeted urban problems based on technical validation and practical experience. Usually, raw data goes through the aforementioned analytical process as an initial evaluation for building a long-term data repository for automated data computing and visualization. Further, such data repositories connect with the automated algorithm for data mining, modeling, or visualization, enabling both numerical output and a portal with a user interface to support data-driven decision-making and operational actions.

It is necessary to point out that urban intelligence proceeds through not a linear but a circular process. Ideally, urban intelligence enables cities to conduct multiple tasks from monitoring to implementation concurrently. In reality, not many cities are capable of real-time data analytics and visualization. Instead, such circular intelligence grows through iterations. For example, the City of New York has been conducting citywide annual building energy consumption benchmarking to better understand energy use intensity, building efficiency, and resultant GHG emissions [14]. Each year, the City collects, analyzes, and reports on building energy consumption data and advises further actions and policies for the next year. Thus, successful data intelligence depends on the effective integration of urban data, analytics, and operations.



**Figure 1.** Conceptual framework of urban intelligence.

In comparison to data intelligence, design intelligence takes more humanistic approaches in the process of innovation and problem-solving. Beyond traditionally defined intelligence emphasizing logical and verbal ability, designers utilize alternative ways of thinking based on perception, graphics, and spatial experience [15]. Design intelligence is a distinctive human competence that can hardly be replaced by machines and algorithms, compared to logical (such as a rule-based algorithm) or verbal (such as voice recognition and communication bots) [16]. In 1993, during the Fourth International Symposium on System Research, Informatics, and Cybernetics, researchers from Lawrence Berkeley Laboratory Energy & Environment Division described that compared to analytical problem-solving, design tackles ill-defined or “wicked” problems and aims to describe a potential situation through graphic representation, physical models, information visualization, computer simulation or others [17]. Traditionally, architects, urban planners, civil engineers, and industrial designers shape the urban built environment using design intelligence. As cities become cyber-physical with information technology and data, design intelligence also determines future cities’ user interface (UI) and user experience (UX).

Crowd intelligence represents collaborative efforts from many individuals through crowdsourcing, social computing, and participation under “a certain Internet-based organizational structure” [18]. In the context of urban intelligence, the word “crowd” has at least two meanings: First, observing a large number of people may reveal underlying patterns or regularities of urban systems, potentially leading to the discovery of new “laws” of cities. Second, “crowd” represents the collective input from the general public as a bottom-up force to shape design, planning, policymaking, and promote wellbeing in cities [19]. In the urban context, crowd intelligence often utilizes information technology to collect data, gather opinions, or mobilize users to conduct environmental monitoring, ecological conservation, informal transportation, or other actions for better quality-of-life, more sustainable, and equitable development in cities. Such nature of urban crowd intelligence brings people, technology, and places together, making cities integrated cyber-physical-social systems.

Urban crowd intelligence can develop either passive or proactive approaches, often with a fusion of passive data mining and proactive participation. A key concept of crowd intelligence is that urban systems become more intelligent from large numbers of digital and human elements, including their interactions [20]. For example, a multidisciplinary team with planners, designers, and computer scientists at MIT initiated a “Digital Matatus” project by mining and visualizing cell phone data to identify informal or semi-formal transportation systems in Nairobi [21]. While this project’s initial data collection process did not rely on a typical crowdsourcing method, aggregation of GTFS (General Transit Feed Specification) data reveals the underlying spatial pattern of informal transportation

systems. Another example is the New York City Tree Census, a participatory data collection project initiated by the NYC Department of Parks & Recreation that involves more than 50,000 volunteers from local communities to collect data on 666,134 street trees [22]. Therefore, urban crowd intelligence either derives from collective behavior revealing physical and social dynamics or as a collection of individual input or feedback.

### 3. Urban Intelligence for Planetary Health

In 2015, the Rockefeller Foundation-Lancet Commission on Planetary Health defined planetary health as “the achievement of the highest attainable standard of health, wellbeing, and equity worldwide through judicious attention to the human systems—political, economic, and social—that shape the future of humanity and the Earth’s natural systems that define the safe environmental limits within which humanity can flourish” [23]. The core philosophy of planetary health is to draw the distinctions between our planet’s health and human public health and emphasize the critical synergy between these two [24]. While planetary health often supports sustainable human development, these two factors do not always share the same momentum. To some extent, “exploitation of the environment has contributed to human health” [25]. As human-being has been enjoying increasing life expectancy with better quality-of-life, technology, and material goods, the earth has been suffering from environmental degradation and collapse of local- or regional-ecosystems. Such conflicts often derive from the evolution of the earth and human development in the process of climate change, natural disasters, and global pandemic.

In 2017, The Rockefeller Foundation and United Nations Framework Convention on Climate Change (UNFCCC) launched a three-year project, “Momentum for Change: Planetary Health”, to promote research innovations to bridge population health and a healthy planet, particularly in issues related to climate change [26]. Regarding how to measure planetary health, the Rockefeller Foundation-Lancet Commission on Planetary Health identifies indicators including population growth, poverty, life expectancy, energy use, water use, domesticated land, fertilizer use, marine fish capture, tropical forest loss, water shortage, ocean acidification, carbon dioxide emissions, temperature change and biodiversity loss [27]. However, due to the large scale and complexity of the earth system, it has been challenging to measure the state of planetary health, especially with real-world data. Cities face both challenges and opportunities in the context of planetary health and must reconsider their roles in shaping future human interactions with the biophysical processes of the earth [28].

Table 1 summarizes the different values, expertise, and applications of three types of urban intelligence. Collectively, they can support cities to address issues involving climate change, global pandemics, and equitable development. The proportion of urban population along with demands for goods and services of urban living make cities account for most environmental impacts with critical responsibility to create greener transportation planning with less GHG emissions and better urban design to promote more sustainable living [29]. One unique aspect of urban intelligence is that it supports both regulation and adaption of cities, either by monitoring, measuring, analyzing, implementing policy related to energy consumption and GHG emissions at the urban scale, or utilizing new information technology for climate change adaptation [30]. With the increasing deployment of large-scale sensing systems, ubiquitous computing enables the collection, analytics, and visualization of high spatial-temporal data on a real-time basis. Such digital capacity empowers cities to better understand complex urban dynamics related to environmental and population health.

**Table 1.** Three types of urban intelligence and their value, domain experts, and applications relevant to planetary health.

	Value	Domain Experts	Applications
Data Intelligence	Extract information and gain knowledge of planetary health factors and their interactions by collecting and integrating various real-world data.	Data scientists, computer scientists, information managers	Urban environment monitoring, human mobility sensing, carbon emission prediction, data-driven decision-making
Design Intelligence	Combines logical, verbal, graphic ability with spatial experience to shape the physical environment and human-machine-environment interface.	Architects, planners, product designers, UI/UX designers	Sustainable urban design, human-machine interaction design, prototype design
Crowd Intelligence	Generate collaborative efforts from a large number of individuals and gain ground truth from local feedbacks.	Public agencies, community-based organizations, civic tech groups	Crowdsourcing, participatory decision-making, community-based acclimate actions

While the causal relationships between planetary health and pandemic are still under investigation, it is undeniable that urban expansion and resultant rainforest loss have brought human habitat and the wild environment with increasingly closer distance and underlying risks of zoonotic disease [31]. Besides guiding long-term strategy and policy for climate change, urban intelligence enables cities to be more responsive with timely actions during an extreme global public health crisis. One unique power of urban intelligence is the connections between information (data intelligence) and people (crowd intelligence) with heterogeneous informational input and various operational output during a public crisis. For the COVID-19 pandemic, urban intelligence provides a more detailed and timely understanding of the movement, facilities, people, information, and engagement in cities to support preventive or responsive operations [32]. Although the United States Centers for Disease Control and Prevention's (CDC) and the World Health Organization (WHO) are reliable information sources for studying infectious diseases, their data suffer from latency, reporting biases, and low resolution, which crowdsourced data may fill the gap of such conventional sources [33]. Considering cities as complex physical-ecological-social-technical systems, a fusion of data-driven culture integrated with community-led efforts provides an additional lens of inspecting and validating urban data and algorithms, addressing underlying disparities and equity issues among different neighborhood areas with various socio-economic conditions.

#### 4. Discussion & Conclusions

For the future development of planetary health, scientists have identified three grand challenges, including (1) the conceptual challenge to understand the conflicts between the prosperity of human society and health of earth systems; (2) the research challenge to identify social-environmental drivers of planetary health through a transdisciplinary approach; and (3) the governance challenges to lead global-scale co-operation and actions [23]. Urban intelligence can support cities with better information integration, analytics, and actions to address the above challenges [34]. From a computational aspect, urban data come from heterogeneous sources with various formats, volumes, and qualities shaped by geographical, historical, political, and cultural factors [35]. Recent studies prove that novel urban data computation utilizing new data sources (e.g., social media, cellphone data, Wi-Fi probe data), unstructured data processing techniques (e.g., natural language processing, imagery, or video data processing), or analytical methods (e.g., machine learning) may provide a more integrated and scalable understanding of how human settlement

interacts with the ecosystem. For example, by integrating the local climate, mosquito and rat species abundance, water and soil condition, demographic and socioeconomic data, an international research group has generated a planetary health model for analyzing key risk factors in informal urban settlements of Indonesia [36]. As a result, this model can provide baseline human well-being measures and enables a surveillance capacity beyond the conventional methods.

In reality, urban data integration is not an easy task that solely relies on technical approaches, but also requires a thoughtful mixture of social and technical considerations [37]. A large portion of urban data represents “digital exhaust”, where the potential uses are often far beyond the original rationale for collecting the data, and the organizational barriers often cause a fragmented urban data landscape as a “data silo” [38]. Although some studies have utilized data mining and integration techniques to handle the data silo problem [39], new concerns arise regarding data representativeness, biases, and resultant algorithmic fairness, partially due to directly analyzing data without engaging the actual collection process [40,41]. Thus, more proactive actions are needed to improve the data collection and analytical process, which often involves people, communities, organizations with non-technical considerations. For example, New York City has established an Automated Decision Systems (ADS) Task Force for reviewing any automated decision systems, a.k.a. algorithms, to ensure they are developed and implemented without projecting harm on any impacted individuals [42]. As a result, better data collection/analytics may capture more diverse aspects of urban living and population groups to improve the fairness and equity of urban intelligence applications [43].

Technical and social considerations are equally critical to ensure the appropriate development and use of urban intelligence, particularly during data integration, analytics, and operation. More holistic and transferrable analytical approaches are needed for transdisciplinary research in complex physical-socio-technical dynamics of urban living across geography [44]. Cities nowadays play an increasingly critical role in shaping civic technology with ethical and thoughtful approaches to ensure that we use urban intelligence for good rather than oppression or discrimination [45]. It is essential to acknowledge the uneven access to technology and digital resources among all population groups, with disparities across geography and society. Thus, future improvements in digitization, quantification, and classification of urban data are needed for better analytics and planning processes to address spatial justice, data representativeness, uncertainty, and algorithmic biases for more equitable design, planning, and operation. Smart city solution providers and data scientists must realize that the long-term societal impact of artificial intelligence is still under preliminary investigation with ongoing conflicts and controversy. The operation of urban intelligence needs to consider the fact that data alone will not make the change, and we need to properly combine information technology with design, policy, and actions.

This article’s contribution is twofold. First, it conceptualizes urban intelligence as an emerging capacity of contemporary cities derived from digital resources (data), domain experts (design), and the general public (crowd). Based on this conceptual framework, it further articulates how such capacity can help cities to be more adaptive and responsive to face the risks in the context of planetary health. Currently, there are alliances including the C40 Cities Climate Leadership Group [46], Global Consortium on Climate and Health Education [47], and the recent Planetary Health Declaration [48] greatly contributes to the collaborations among international cities. Nevertheless, urban intelligence only partially exists in a few rich and well-developed cities, primarily within the scope of an individual city. More partnerships on urban intelligence are needed in the future to support information exchange protocol, open data standards, policy alliances, and a long-term synergy of actions at both local- and global-scale [49]. This research may support a global consortium of urban intelligence for planetary health by promoting collective worldwide urban intelligence in the future.

As cities are increasingly driving the forces that shape the future of human and environmental development, urban intelligence will contribute to better understandings

and actions on planetary health, especially in the context of climate change and the global pandemic. While many cities have started to explore the potential applications of urban intelligence, more future work is needed for understanding the various driving forces and cultural contexts that shape cities across regions, so we can further identify the potential common ground for collaborations and actions at a global scale.

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