smart cities

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Perspective

Redefining the Use of Big Data in Urban Health for Increased Liveability in Smart Cities

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Received: 7 June 2019; Accepted: 19 June 2019; Published: 22 June 2019

Abstract: Policy decisions and urban governance are being influenced by an emergence of data from internet of things (IoT), which forms the backbone of Smart Cities, giving rise to Big Data which is processed and analyzed by Artificial Intelligence models at speeds unknown to mankind decades ago. This is providing new ways of understanding how well cities perform, both in terms of economics as well as in health. However, even though cities have been increasingly digitalized, accelerated by the concept of Smart Cities, the exploration of urban health has been limited by the interpretation of sensor data from IoT devices, omitting the inclusion of data from human anatomy and the emergence of biological data in various forms. This paper advances the need for expanding the concept of Big Data beyond infrastructure to include that of urban health through human anatomy; thus, providing a more cohesive set of data, which can lead to a better knowledge as to the relationship of people with the city and how this pertains to the thematic of urban health. Coupling both data forms will be key in supplementing the contemporary notion of Big Data for the pursuit of more contextualized, resilient, and sustainable Smart Cities, rendering more liveable fabrics, as outlined in the Sustainable Development Goal (SDG) 11 and the New Urban Agenda.

Keywords: big data; urban health; smart cities; medical data; artificial intelligence; internet of things (IoT); liveability

1. Introduction

Efforts in rendering urban centers more liveable has yielded numerous positive and rewarding results, and the role of technology is known to have accelerated this process; leading to an increase in the number of smart cities globally aimed at achieving increased liveability [1,2]. These lead to improvement in service delivery, seamless traffic flow, and data and information sharing, amongst others. The monitoring of critical issues like the weather patterns, mobility, emissions, sanitation, security, and land use has been greatly improved, and real-time solutions have been designed and implemented in various cities [3]. The monitoring of these issues has enabled the use of advanced technologies such as Big Data, IoT, and Artificial Intelligence, as promoted by the Smart Cities concept [1,4]. The health sector is amongst those that have greatly benefited from the advent of Big Data; generated by data collection from a wide network of sensors riding on IoT platforms and protocols [5].

A report by McKinsey and Company [6] showcases how the health sector gained from these installations and shows that, through Big Data and smart sensors, it is now possible to monitor patients remotely, receive first aid alerts and real-time information on air quality, temperature, and others, receive alerts on looming natural disasters like flooding and earthquakes that cause bodily injuries, and allows for surveillance of infectious diseases. Those data add to render informed decisions in the advent of a crisis and offer better urban management tools [4,7,8]. The use of data in this fashion is increasingly relevant for the health sector in urban centers, as health is known to be influenced by different issues like traffic, energy generation, waste generation, and production, and the availability of green spaces, water, and food. Cook, et al. [9] further argue that smart city infrastructures are supporting smarter healthcare, especially by increasing its effectiveness by capitalizing on real-time data generated by these infrastructures. They found that the availability of mobile and ambient sensors enabled by machine learning, which is part of the IoT, is key to this improvement. In particular, the interlinkage of these infrastructures allows for data collaboration and sharing that can be further improved for enabling data privacy, a sensitive area in the health sector [10,11]. With quality and secured data, concerted action to address health concerns has become easier and more efficient. Coupled with other dimensions like the economy, society, and environment, this creates a more resilient grid tailored towards the improvement of urban liveability.

To affirm and qualify the above assertion of the benefits of the health sector to other urban fabric, numerous studies converge toward the conclusion that improved health sectors forms the pinnacle of a liveable city [12–14]. Nevertheless, despite this fact, the concept of urban health in most Smart Cities is limited in its design and is restrictive when it comes to data collection from sensors, as they target only infrastructural data, and thus work in disconnection with the advances of the medical sector. In this vein, since the concept of smart cities is a work in progress [15,16], the Big Data gained need to be aligned with modern medical practices through the careful and seamless integration of the medical field in the planning and further actualization of the Smart City concept.

2. Urban Health and the Emergence of Data

The landscape of current urban evolution and the prevalence of Smart Cities have promoted a data-centric society. From real-time traffic predictions to personalized fitness tracking, the advancement in technologies and the emergence of data from various fields, as noted above, is influencing the health sector. Data generation pertaining to urban health is coming from several directions. In the medical science, there is a notable increase in research in various fields such as genetics, infectious, and noninfectious diseases, wellness and fitness, ageing, and pharmaceuticals, amongst many others [17–19]. With this, a substantial amount of data is routinely generated; providing for vital advancement in preventive care and treatment [20]. Fatt and Ramadas [21] posit that the Big Data garnered has allowed for prevention of morbidity and mortality through adequate prediction of health and disease outcomes and the management of outbreaks. Indirect urban health-related data are also generated constantly via established components of the modern city. Examples are traffic and pollution monitoring, disease surveillance, and natural catastrophe monitoring. Senthilkumar, et al. [22] advance that the use of Big Data now enables stakeholders to prospect on future needs and trends; hence, planning in advance. Technology has allowed the generation process of Big Data to increase in volume, velocity, and variety as well as improve in veracity, variability, and value, all to the benefit of the health sector [7]. As shared by McKinsey and Company [6], data has provided patients with added benefits such as rights to living, care, value, and professional services coupled with cutting edge innovation. This argument is supported by Schlick, et al. [23] who express how cancer patients are now receiving quality care as courtesy of Big Data collected and shared from different medical fields. See, et al. [24] further this notion by showcasing that Big Data has the potential to allow error-free medical prescription by enhancing the administration of precise medicine for particular cases. Mehta and Pandit [25] share the same view and add that Big Data can help in the reduction of wastage in healthcare sectors as well as improving the quality and reducing associated costs to care.

Though these myriads of datasets have been generated via the same Big Data technologies that power the concept of smart cities, a majority of them are being used primarily towards the advancement of the medical field alone or towards urban monitoring alone. Little effort has been made to dwell in those datasets and understand the synergies between people (as a physiological entity) and cities. An explanation to this could be the sensitive and confidential nature of medical data that call for the highest levels of privacy and security when being shared, exchanged, and used; especially for cross-sectorial initiatives and for purposes beyond the medical sector only. However, in those instances where datasets have been used for collaboration across different sectors, fascinating insights have emerged. Examples being the relationship between DNA and migration patterns and also the link between microbiomes and health and culture. Greenaway and Castelli [26] explain that identifying and understanding the movement of microbes is vital to the medical sphere, especially in deciphering and explaining the occurrence of certain traits or disease in a given region. Further to this, Azmak, et al. [27] argue that medical datasets have the potential to unveil the biological make up of human groups and explain how this influences behaviors and lifestyles. Similarly, it has the potential to reveal why and how different groups of people in a given area are impacted by environmental conditions and the implications of altering their environment; hence, allow for the improvement of their health and quality of life. Medical data thus has the potential to reveal why certain medical conditions are geographically tied [28], and coupled with other datasets, with the help of Artificial Intelligence (AI), those could garner even larger and more effective predictive tools.

3. Classification of Urban Health & Medical Data

From the above literature, it is noted that most of the Big Data that shapes urban health is obtained from the interpretation of results from two main avenues—sensors installed in cities and medical data. Sensors used as part of modern urban set ups produce large amounts of data that can be harnessed towards the improvement of urban health. In this case however, engagement with the data is limited to the way data is garnered and analyzed. Yet, the quality and relevance of this data cannot be discredited given the implementation of a wide array of sensors generating a sizeable amount of data relating to health. These sensors range from those dedicated to traffic to those in energy sectors, and they have the potential to capture data on parameters like atmospheric emissions and casualties, in case of accidents. Other sensors record information about temperature, humidity, wind speed and direction, and rainfall. While those directly pertain to the field of urban climate, they are equally adaptable and often significantly used in urban health models. Table 1 below summarizes the different dimensions from which urban health data is garnered.

Table 1. Dimensions frequently factored in urban health.

	Relative Humidity	Emissions	Temperature	Wind	Precipitation	Traffic Emissions & Casualties	Waste	Water Quality	Noise	UV Index
José, et al. [29]		x	X							
Liu1, et al. [30]	x	X	X		X					
Nadrian, et al. [31]		X				X				
Nayak [32]		X				X				
McKinsey & Company [6]	X	X	X	X	X	X	X	X		
Hanckle, et al. [33]					X			X		
Alvear, et al. [34]	X		X							
Wong, et al. [35]	X	X	X						X	X
Peckens, et al. [36]									X	
Segura-Garcia, et al. [37]									X	
Zhao, et al. [38]	X	X	X	X						
Deo, et al. [39]										X
Ekeu-wei, et al. [40]		X					X			
Bačić, Jogun and Majić [5]	X	X	X	X	X	X	X	X	X	X

The use of medical data to explore urban health depends largely on the presence of baseline datasets that are routinely managed and report burden of disease (BoD) and mortality patterns in urban populations. Advents of worldwide datasets such as the Global Burden of Disease (Lopez, et al. [41]) provide important indicators to monitor health at city levels. The links between medical data and cities are then made possible using tools and integrated methods such as health impact assessments (HIA), health risk assessments (HRA), and burden of disease assessments (BoDA). Various studies explore the health impacts of urban environment on the health of urban environment by analyzing the benefits of active behaviors and pitfalls of pertaining to low-income populations and being confronted with risky exposure pathways [42–44]. Different types of medical data have been used to predict outcomes relevant to urban health including the prevalence of communicable and noncommunicable diseases, hospital admission rates, levels of physical activity, food consumption, and access to water, sanitation, and hygiene (WASH) services. Table 2 below summarizes data types in the medical field that have a correlation with the urban field and could be collected through various means through the array of IoT devices installed in Smart Cities.

Table 2. Identified medical datasets that could be coupled with Smart City-collected data from IoT (internet of things).

	Noncommunicable Diseases Diagnosis	Communicable Diseases Diagnosis	Disease Specific Mortality	Total Mortality	Hospital Admissions	Outpatient Visits	Emergency Visits	WASH	Physical Activity	Nutrition
Liu, et al. [45]		x			x	x				
Tashayo, et al. [46]			x	x						
Hayajneh, et al. [47]	x									
Guttikunda and Khaliquzzaman [48]	x			x	x		x			
Rojas-Rueda, Audrey de Nazelle and Nieuwenhuijsen [44]				x				x		
Mueller, et al. [49]				x					x	
Tainio, et al. [50]				x					x	x
Zapata-Diomedi, et al. [51]									x	

4. An Agenda for Redefining Urban Health

There is no single best way of organizing and addressing the complex links between environment, urban development, and health [52]. However, the use of data from the medical sector provides a possible entry point to enhance positive urban health actions and outcomes. First, the consideration of disease prevalence data provides a useful and detailed measure of the risk to which populations are exposed. For example, a study estimating the risk of exposure to heavy metals from the food consumption in urban areas of Westmidlands (UK) goes as far as defining site-specific health risks using high-definition maps of sensitivity and maps the risks following specific subpopulation groups [53]. Similarly, the analysis of fecal samples and medical home visits in urban Brazilian children provided a detailed understanding of the common pathogens causing incidence of diarrhea prevalence in "sentinel" areas and vulnerable populations [54].

Second, medical data such as levels of physical activity provides an opportunity to explore a variety of aspects related to economic, social, and ecological factors associated with urban living. In short, medical data has potential to provide a subtle understanding of the environment where urban initiatives and realities take place. Using a health impact modelling tool focused on cities, Woodcook and his team show that it is indeed possible to achieve health benefits while reducing greenhouse gas emissions from transport, resulting in a policy win–win scenario [55]. From a methodological perspective, both environmental data (carbon dioxide emissions) and health data (physical activity and traffic injury) were modelled simultaneously to understand the estimated health impacts in urban settings of Wales and England, with a particular focus on individual diseases faced by population groups.

Third, the management of urban risks using health data can be, and is increasingly, associated with economic benefits. Guttikunda and Khaliquzzaman [48] show that integrating health data in the urban narrative can enable one to consider effective cost gains and losses in terms of restricted day activities and annual health losses [48]. Particularly, the economic costs of health risk to cities are being expressed with convertible units such as DALYS (disability adjusted life years), WTP (willing to pay), and YLLs (years of life lost) due to diseases. For instance, in Istanbul Turkey, a study calculated the DALYS related to noise pollution, air pollution, and impact of the emission of greenhouse gases and found that in 2010, 87,471 years of life lost (YLL) occurred due to cardiovascular disease in nine urban municipalities [56]. In Bangkok (Thailand), Li and Crawford-Brown [57] estimated that in year 2000 the total health damage cost due to exposure to traffic-related fine particulate matter was 2678 million U.S. dollars in the Bangkok Metropolitan area and that premature deaths accounted for 1369.2 million dollars or 51.1% of the total health damage costs. Their results further indicated that the economic loss due to exposure to PM10 emissions from transportation in the capital city alone accounted for about 2.35% of Thailand's gross domestic product (GDP) [57]. The economic dimension can however be designed to ensure that those inclusions are catered by the private sector, through the Information Communication Technology (ICT) organizations that will ultimately install those sensors and process the generated data [58].

Therefore, besides expanding data collection from infrastructure to the medical field in Smart Cities and allowing data analysis, while keeping sensible privacy controls, furthering an agenda for redefining urban health will have to consider and integrate at least three major benefits, summarized as the ability to (1) conduct more sensitive and detailed risk and impact assessments, (2) complete studies providing a more subtle and holistic understanding of urban realities while adapting methods to socioeconomic and environmental contexts, and finally (3) converting health risks and outcomes into monetary gains and loss, which in turn can drive strategic economic profitability in cities.

5. Conclusions

The advent of the digital revolution has fueled an increased use of data in cities with the aim to sharpen the efficiency and liveability of urban fabrics; whereby the concept of Smart Cities has gained in popularity and emerged as a potent solution for the current challenges of our time. However, despite the direct linkages between the thematic of urban health and the dimension of liveability, health has received little attention in Smart City policy frameworks when it comes to the adoption of holistic and cross-sectorial approaches merging medical and infrastructural data collected from IoT solutions. One notable challenge to this is the need to define strict protocols, as health data may not be available or accessible due to its complex, confidential, or sensitive nature. This paper further showcases that there are in fact synergies that can be achieved from the association of various datasets, and this can further our knowledge on the relationship of people and cities and lead to complementary commercial activities if the proper fiscal mechanisms are put in place.

Author Contributions: Conceptualization, formal analysis, investigation & writing, Z.A, H.T & M.T.

Funding: No funding was received for this study

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Allam, Z. Building a conceptual framework for smarting an existing city in Mauritius: The case of port louis. *J. Biourbanism* **2017**, *4*, 103–121.
2. Allam, Z.; Newman, P. Redefining the smart city: Culture, metabolism & governance. *Smart Cities* **2018**, *1*, 4–25.
3. Allam, Z.; Dhunny, Z.A. On big data, artificial intelligence and smart cities. *Cities* **2019**, *89*, 80–91. [CrossRef]
4. Allam, Z. Contextualising the smart city for sustainability and inclusivity. *New Des. Ideas* **2018**, *2*, 124–127.
5. Bačić, Ž.; Jogun, T.; Majić, I. Integrated Sensor Systems for Smart Cities. *Tehnički Vjesnik* **2018**, *25*, 277–284.
6. McKinsey&Company. *Smart Cities: Digital Solutions for a More Liveable Future*; McKinsey&Company: Brussel, Belgium, 2018; pp. 1–152.
7. Allam, Z. On smart contracts and organisational performance: A review of smart contracts through the blockchain technology. *Rev. Econ. Bus. Stud.* **2018**, *11*, 137–156. [CrossRef]
8. Allam, Z.; Dhunny, Z.A.; Siew, G.; Jones, D. Towards smart urban regeneration: Findings of an urban footprint survey in Port Louis, Mauritius. *Smart Cities* **2018**, *1*, 121–133. [CrossRef]
9. Cook, D.J.; Duncan, G.; Sprint, G.; Fritz, R.L. Using Smart City Technology to Make Healthcare Smarter. *Proc. IEEE* **2018**, *106*, 708–722. [CrossRef]
10. Huang, Q.; Wang, L.; Yang, Y. Secure and Privacy-Preserving Data Sharing and Collaboration in Mobile Healthcare Social Networks of Smart Cities. *Hindawi Secur. Commun. Netw.* **2017**, *2017*, 6426495. [CrossRef]
11. Huang, H.; Gong, T.; Ye, N.; Wang, R.; Dou, Y. Private and Secure medical data transmission and analysis for wireless sensing healthcare systems. *IEEE Trans. Ind. Inf.* **2017**, *13*, 1227–1237. [CrossRef]
12. Garau, C.; Pavan, V.M. Evaluating Urban Quality: Indicators and Assessment Tools for Smart Sustainable Cities. *Sustainability* **2018**, *10*, 575. [CrossRef]
13. Caird, S.P.; Hallett, S.H. Towards evaluating desing for smart city development. *J. Urban Des.* **2018**, *24*, 188–209. [CrossRef]
14. Ibrahim, M.; El-Zaart, A.; Adams, C. Smart Sustainable Cities roadmap: Readiness for transformation towards urban sustainability. *Sustain. Cities Soc.* **2018**, *37*, 530–540. [CrossRef]
15. Silva, B.N.; Khan, M.; Han, K. Towards sustainable smart cities: A review of trends, architecutures, components, and open challenges in smart cities. *Sustain. Cities Soc.* **2018**, *38*, 697–713. [CrossRef]
16. Allam, M.Z. *Redefining Thesmart City: Culture, Metabolism and Governance. Case Study of Port Louis, Mauritius*; Curtin University: Perth, Australia, 2018.
17. Islam, M.; Hasan, M.; Wang, X.; Germack, H.; Noor-E-Alam, M. A Systematic Review on Healthcare Analytics: Application and Theoritical Perspective of Data Mining. *Healthcare* **2018**, *6*, 54. [CrossRef] [PubMed]
18. Bayne, L.E. Big Data in Neonatal Health Care: Big Reach, Big Reward? *Crit. Care Nurs. Clin. N. Am.* **2018**, *30*, 481–497. [CrossRef]
19. Arjan, J.; de Visser, G.M.; Elena, S.F.; Fragata, I.; Matuszewski, S. The utility of fitness landscapes and big data for predicting evolution. *Heredity* **2018**, *121*, 401–405.
20. Ristevski, B.; Chen, M. Big Data Analytics in Medicine and Healthcare. *J. Integr. Bioinform.* **2018**, *15*, 20170030. [CrossRef]
21. Fatt, Q.K.; Ramadas, A. The Usefulness and Challenges of Big Data in Healthcare. *J. Healthc. Commun.* **2018**, *3*, 21–25. [CrossRef]

22. Senthilkumar, S.A.; Rai, B.K.; Meshram, A.A.; Gunasekaran, A.; Chandrakumarmangalam, S. Big Data in Healthcare Management: A Review of Literature. *Am. J. Theor. Appl. Bus.* **2018**, *4*, 57–69.
23. Schlick, C.J.; Castles, J.P.; Bentrem, D.J. Utilizing Big Data in Cancer Care. *Surg. Oncol. Clin. N. Am.* **2018**, *27*, 641–652. [CrossRef] [PubMed]
24. See, H.-Q.; Chan, J.-N.; Ling, S.-J.; Gan, S.-C.; Leong, C.-O.; Mai, C.-W. Advancing Pharmacy Service using Big Data—Are We Fully Utilising the Big Data's Potential Yet? *J. Pharm. Pharm. Sci.* **2018**, *21*, 217–221. [CrossRef] [PubMed]
25. Mehta, N.; Pandit, A. Concurrence of big data analytics and healthcare: A systematic review. *Int. J. Med. Inf.* **2018**, *114*, 57–65. [CrossRef] [PubMed]
26. Greenaway, C.; Castelli, F. Migration medicine. *Infect. Dis. Clin. N. Am.* **2019**, *33*, 265–287. [CrossRef]
27. Azmak, O.; Bayer, H.; Caplin, A.; Glimcher, P.; Koonin, S.; Patrinos, A. Using Big Data to Understand the Human Condition: The Kavli HUMAN Project. *Big Data* **2015**, *3*, 173–188. [CrossRef] [PubMed]
28. Moustafa, A.A.; Diallo, T.M.O.; Amoroso, N.; Zaki, N.; Hassan, M.; Alashwal, H. Applying Big Data Methods to Understanding Human Behavior and Health. *Front. Comput. Neurosci.* **2018**, *12*, 84. [CrossRef] [PubMed]
29. José, R.S.; Pérez, J.L.; Pérez, L.; Maria, R.; Barras, G. Effects of climate change on the health of citizens modelling urban weather and air pollution. *Energy* **2018**, *165*, 53–62. [CrossRef]
30. Liu1, L.; Yang, X.; Wang, M.; Yong Long, H.S.; Nie, Y.; Chen, L.; Guo, H.; Jia, F.; Nelson, J.; Song, G.; et al. Climate Change, Air Quality and Urban Health: Evidence from Urban Air Quality Surveillance System in 161 Cities of China 2014. *J. Geosci. Environ. Prot.* **2018**, *6*, 117–130. [CrossRef]
31. Nadrian, H.; Taghdisi, M.H.; Aghemiri, M.; Khazaee-Pool, M.; shojaeizadeh, D. Impacts of Urban Traffic Jams on Physical Health of Residents from the Inhabitants 'Perspective in Sanandaj City: A Qualitative Study. *J. Health Educ. Health Promot.* **2017**, *5*, 345–358. [CrossRef]
32. Nayak, J. Round the Clock Vehicle Emission Monitoring using IoT for Smart Cities. *Int. J. Adv. Comput. Sci. Appl.* **2018**, *9*, 616–619. [CrossRef]
33. Hanckle, G.P.; Silva Bde, C.; Hackle, H.P. The role of Advanced Sensing in Smart Cities. *Sensors* **2013**, *13*, 393–425. [CrossRef] [PubMed]
34. Alvear, O.; Calafate, C.T.; Cano, J.C.; Manzoni, P. Crowdsensing in Smart Cities: Overview, Platforms, and Environmental Sensing Issues. *Sensors* **2018**, *18*, 460. [CrossRef] [PubMed]
35. Wong, M.S.; Wang, T.; Ho, H.C.; Kwok, C.Y.T.; Lu, K. Towards a Smart City: Development and Application of an Improved Integrated Environmental Monitoring System. *Sustainability* **2018**, *10*, 623. [CrossRef]
36. Peckens, C.; Porter, C.; Rink, T. Wireless Sensor Networks for Long-Term Monitoring of Urban Noise. *Sensors* **2018**, *18*, 3161. [CrossRef] [PubMed]
37. Segura-Garcia, J.; Felici-Castell, S.; Perez-Solano, J.J.; Navarro, J.M.; Cobos, M. Low-Cost Alternatives for Urban Noise Nuisance Monitoring Using Wireless Sensor Networks. *IEEE Sens. J.* **2015**, *15*, 836–844. [CrossRef]
38. Zhao, Z.; Wang, J.; Fu, C.; Liu, Z.; Liu, D.; Li, B. Design of a Smart Sensor Network System for Real-Time Air Quality Monitoring on Green Roof. *J. Sens.* **2018**, *2018*, 1987931. [CrossRef]
39. Deo, R.C.; Downs, N.; Parisi, A.V.; Adamowski, J.F.; Quilty, J.M. Very short-term reactive forecasting of the solar ultraviolet index using an extreme learning machine integrated with the solar zenith angle. *Environ. Res.* **2017**, *155*, 141–166. [CrossRef]
40. Ekeu-wei, I.T.; Azuma, K.I.; Ogunmuyiwa, F.B.B. Assessement of Environmental Impact of Solid Waste Dumpsites Using Remote Sensing. *Niger. J. Technol.* **2018**, *37*, 275–285. [CrossRef]
41. Lopez, A.D.; Mathers, C.D.; Ezzati, M.; Jamison, D.T.; Murray, C.J. Global and regional burden of disease and risk factors, 2001: Systematic analysis of population health data. *Lancet (London)* **2006**, *367*, 1747–1757. [CrossRef]
42. Corburn, J. Confronting the Challenges in Reconnecting Urban Planning and Public Health. *Am. J. Public Health* **2004**, *94*, 541–546. [CrossRef]
43. Northridge, M.E.; Sclar, E. A Joint Urban Planning and Public Health Framework: Contributions of Health Impact Assessment. *Am. J. Public Health* **2003**, *93*, 118–121. [CrossRef] [PubMed]
44. Rojas-Rueda, D.; Audrey de Nazelle, M.T.; Nieuwenhuijsen, M.J. The Health Risks and Benefits of Cycling in Urban Environments Compared with Car Use: Health Impact Assessment Study. *BMJ Open* **2011**, *343*, d4521. [CrossRef] [PubMed]

45. Liu, N.; Yen, C.; Fang, Z.-Y.; Tate, J.E.; Jiang, B.; Parashar, U.D.; Zeng, G.; Duan, Z.-J. Projected health impact and cost-effectiveness of rotavirus vaccination among children <5 years of age in China. *Vaccine* **2012**, *30*, 6940–6945.
46. Tashayo, B.; Alimohammadi, A.; Sharif, M. A Hybrid Fuzzy Inference System Based on Dispersion Model for Quantitative Environmental Health Impact Assessment of Urban Transportation Planning. *Sustainability* **2017**, *9*, 134. [CrossRef]
47. Hayajneh, W.A.; Daniels, V.J.; James, C.K.; Kanıbir, M.N.; Pilsbury, M.; Marks, M.; Goveia, M.G.; Elbasha, E.H.; Dasbach, E.; Acosta, C.J. Public health impact and cost effectiveness of routine childhood vaccination for hepatitis a in Jordan: A dynamic model approach. *BMC Infect. Dis.* **2018**, *18*, 119. [CrossRef] [PubMed]
48. Guttikunda, S.K.; Khaliquzzaman, M. Health benefits of adapting cleaner brick manufacturing technologies in Dhaka, Bangladesh. *Air Qual. Atmos. Health* **2014**, *7*, 103–112. [CrossRef]
49. Mueller, N.; Rojas-Rueda, D.; Basagaña, X.; Cirach, M.; Cole-Hunter, T.; Dadvand, P.; Donaire-Gonzalez, D.; Foraster, M.; Gascon, M.; Martinez, D.; et al. Urban and Transport Planning Related Exposures and Mortality: A Health Impact Assessment for Cities. *Environ. Health Perspect.* **2017**, *125*, 89–96. [CrossRef]
50. Tainio, M.; Monsivais, P.; Jones, N.R.V.; Brand, C.; Woodcock, J. Mortality, greenhouse gas emissions and consumer cost impacts of combined diet and physical activity scenarios: A health impact assessment study. *BMJ Open* **2017**, *7*, e014199. [CrossRef]
51. Zapata-Diomedi, B.; Herrera, A.M.; Veerman, J.L. The effects of built environment attributes on physical activity-related health and health care costs outcomes in Australia. *Health Place* **2016**, *42*, 19–29. [CrossRef]
52. Joffe, M.; Mindell, J. A framework for the evidence base to support Health Impact Assessment. *J. Epidemiol. Commun. Health* **2002**, *56*, 132. [CrossRef]
53. Hough, R.L.; Breward, N.; Young, S.D.; Crout, N.M.J.; Tye, A.M.; Moir, A.M.; Thornton, I. Assessing potential risk of heavy metal exposure from consumption of home-produced vegetables by urban populations. *Environ. Health Perspect.* **2004**, *112*, 215–221. [CrossRef] [PubMed]
54. Barreto, M.L.; Milroy, C.A.; Strina, A.; Prado, M.S.; Leite, J.P.; Ramos, E.A.; Ribeiro, H.; Alcantara-Neves, N.M.; Teixeira Mda, G.; Rodrigues, L.C.; et al. Community-based monitoring of diarrhea in urban Brazilian children: Incidence and associated pathogens. *Trans. R. Soc. Trop. Med. Hyg.* **2006**, *100*, 234–242. [CrossRef] [PubMed]
55. Woodcock, J.; Givoni, M.; Morgan, A.S. Health Impact Modelling of Active Travel Visions for England and Wales Using an Integrated Transport and Health Impact Modelling Tool (ITHIM). *PLoS ONE* **2013**, *8*, e51462. [CrossRef] [PubMed]
56. Ongel, A.; Sezgin, F. Assessing the effects of noise abatement measures on health risks: A case study in Istanbul. *Environ. Impact Assess. Rev.* **2016**, *56*, 180–187. [CrossRef]
57. Li, Y.; Crawford-Brown, D.J. Assessing the co-benefits of greenhouse gas reduction: Health benefits of particulate matter related inspection and maintenance programs in Bangkok, Thailand. *Sci. Total Environ.* **2011**, *409*, 1774–1785. [CrossRef] [PubMed]
58. Allam, Z.; Jones, D.S. Attracting investment by introducing the city as a special economic zone: A perspective from Mauritius. *Urban Res. Pract.* **2019**, 1–7. [CrossRef]