Environmental influences on behaviour and health: a call for creativity and radical shifts in thinking within contemporary research

Matthew Hobbs, James Atlas

In 2050, 68% of the world's population will reside in urban areas.[1] As suggested by a recent *Lancet* series, urbanisation represents a significant challenge for future populations.[2] While influences on human behaviour are multidimensional, adverse urban environments are increasingly considered linked, within policy and research, to unfavourable behaviours and outcomes such as an increased prevalence of diabetes.[3] Despite intuitive appeal and policy action, evidence linking environments to such health outcomes is often cross-sectional, plagued by persistent methodological limitations and findings are thus equivocal.[4] Evidential inconsistency has not improved over time, most likely due to research, including our own,[5] assuming that environments impact directly upon such health outcomes. Prominent scholars have also persistently questioned our inadequate understanding of how urban environments impact on behaviour.[6]

Methods linking environments to behaviour and health have stagnated and are so diverse, they restrict the possibility of evidence being translated into policy.[4] Understanding has likely not improved significantly due to persistent field-wide methodological limitations,[4] including our inability to maximise experimental control in complex social situations and environments. These persistent limitations justify a need for creativity and a consideration of new approaches in an era of big data[7] for instance, using new methods such as deep learning, virtual reality and reinforcement learning. While such methods have the potential to advance public health practice and policy, they are seldom, if ever, applied. We call for researchers to consider using these approaches to advance knowledge in this field of science and beyond.

The ambitious use of new methods such as deep learning methods[8] have been encouraged as they enable researchers to better understand problems using unfamiliar methods not considered before in the field.[9] Deep learning methods, such as previously trained convolutional neural networks (CNNs) can now exploit the ubiquity of digital imagery, automated data analyses, and improvements in machine vision techniques to automate the extraction of features, classification of objects and environmental measurements, ie, cycleways or pollution. For instance, a pioneering study which used deep learning to extract different aspects of the environment, such as greenery and different housing types, from high resolution satellite imagery promisingly showed that extracted features of the built environment explained 72% to 90% of the variation in obesity prevalence across cities in the US.[8] While deep learning methods could also be applied to various research scenarios globally, they are still limited by an inability to expose individuals to adverse environments within a controlled setting.

Virtual reality is just another example of a new method which could be used in original scenarios to rigorously and creatively investigate the mechanism by which adverse urban environments are linked to behaviour. Virtual reality is promising as it overcomes the persistent

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limitation that intentionally exposing participants to adverse environments is not ethically possible.[6] Importantly, virtual reality software and hardware is becoming more accessible due to improvements in technology. It also uniquely offers ecological and internal validity as features in adverse urban environments can be closely controlled for experimental purposes, maximising experimental control in a traditionally complex situation and environment.

Reinforcement learning offers another potential method to assist policy making.[10] The search space of possible changes to an environment that might impact public health is large, especially when contextualised in a specific urban zone. Reinforcement learning includes methods and algorithms that can generate policies based on human practices, transfer these to new environments, simulate virtual agent rewards and iteratively adjust the policies using experimental feedback. This approach specifically balances and models the cost of exploring a new policy versus the optimisation of current policies. Moreover, it can advise new studies and local implementation or expand existing studies to engineer environments. Using such an approach may help overcome the limitation of needing years to plan and conduct longitudinal studies.

The availability of large-scale computation to test these novel models on large data provides a compelling call to apply them to environmental studies and broader fields of public health. There are challenges associated with the use of such novel methods with a reliance on interdisciplinary research and collaboration. However, if the power of these approaches is harnessed successfully then they have the potential to advance public health practice and policy making worldwide and transform thinking within other fields of science.

Competing interests:

Nil.

Author information:

Matthew Hobbs, Geohealth Laboratory, University of Canterbury, Christchurch;
James Atlas, Department of Computer Science, University of Canterbury, Christchurch.

Corresponding author:

Dr Matthew Hobbs, Geohealth Laboratory, University of Canterbury, Christchurch.
matt.hobbs@canterbury.ac.nz

URL:

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