AI-Enabled Climate–Health Nexus Framework for Decision-Support in Sustainable Urban Green Infrastructure

Phoebe Xu[1], Jinying Xu[2], Jeff Clark[3], and Ravi Shankar[4]

[1]School of Civil, Aerospace and Design Engineering, University of Bristol, UK
[2]College of Design and Engineering, National University of Singapore, Singapore
[3]School of Engineering Mathematics and Technology, University of Bristol, UK
[4] Clinical Research & Innovation Office, Tan Tock Seng Hospital, Singapore

[1]phoebe.xu@bristol.ac.uk, [2]jinying.xu@nus.edu.sg, [3]jeff.clark@bristol.ac.uk, [4]ravisr.srivastava@gmail.com

Abstract

Urban green infrastructure is increasingly recognised as a critical component of sustainable and resilient cities. However, planning and construction decisions often fail to capture the coupled impacts of environmental performance and human behaviour in a systematic and quantitative manner. This paper presents an AI-enabled Climate-Health Nexus (CHN) framework that integrates behavioural data, environmental indicators and carbon metrics to support decision-making for urban green space interventions. Using real-world datasets from NHS green social prescribing programmes and municipal open data, the framework employs machine learning models to simulate behavioural responses to interventions such as improved walking infrastructure, shaded seating and community gardening. These behavioural changes are translated into measurable carbon and energy impacts, including reduced pharmaceutical demand, lower household energy consumption and modal shifts towards active travel. The proposed framework functions as a digital decision-support system, enabling rapid comparison and optimisation of intervention scenarios under different urban conditions. A prototype CHN Index is developed to quantify combined climate and wellbeing outcomes, providing decision-quality metrics for planners and infrastructure stakeholders. The results demonstrate how behavioural dynamics can be operationalised through AI-driven simulation to inform sustainable, smart and lean urban construction and planning.

Keywords –

AI simulation; Decision-Support Systems; Sustainable Urban Infrastructure; Behavioural Modelling; Digital Twins

1 Introduction

Cities face increasing pressure to deliver low-carbon, climate-resilient and socially inclusive urban environments. Urban green infrastructure has been widely promoted as a key strategy to mitigate climate risks, reduce emissions and improve population wellbeing [1,3,11–13]. Despite this recognition, the planning and construction of green infrastructure are often guided by fragmented assessments that treat environmental performance, human behaviour and health outcomes in isolation. This fragmentation limits the ability of decision-makers to identify interventions that deliver combined benefits across climate, energy and wellbeing dimensions.

Recent advances in automation, artificial intelligence (AI) and data-driven modelling offer new opportunities to integrate complex behavioural and environmental dynamics into urban infrastructure decision-making. Within the construction and built environment domain, AI-enabled digital twins and simulation frameworks have been increasingly applied to optimise energy use, construction logistics and operational performance [2,4–7]. However, behavioural pathways, such as changes in activity patterns, healthcare demand or lifestyle choices triggered by built environment interventions, remain underrepresented in these models [1].

This paper addresses this gap by proposing an AI-enabled CHN framework that explicitly links urban green infrastructure interventions to behavioural change and downstream carbon and energy impacts. The framework is designed as a decision-support system for sustainable urban planning and construction, enabling rapid simulation and comparison of intervention scenarios. The primary contribution of this work lies in the conceptual and methodological integration of behavioural modelling, carbon accounting and wellbeing assessment within an AI-enabled decision-support framework for urban green infrastructure. Rather than proposing a novel machine learning algorithm, the study advances the application of interpretable AI techniques to operationalise behavioural–climate linkages within infrastructure planning. The key contributions of this work are threefold: (1) the development of a unified AI-driven framework that integrates behavioural, environmental and carbon indicators; (2) the operationalisation of behavioural change pathways, including healthcare and energy-related effects, within a simulation-based decision-support system; and (3) a real-world case study demonstrating the applicability of the framework using urban data from Bristol, UK.

2 Related Work

AI and automation have played an increasingly prominent role in sustainable construction and urban infrastructure planning. Digital twins, machine learning-based energy models and optimisation algorithms have been used to improve building performance, construction efficiency and urban energy management, enabling scenario testing and performance forecasting across the lifecycle of built assets [2,4–6]. Digital twin concepts have increasingly been adopted in construction and urban systems to integrate data, simulation and decision-making across the asset lifecycle [4,5,7].

In parallel, research in urban design and public health has demonstrated the positive effects of green infrastructure on physical activity, mental wellbeing and social cohesion. Initiatives such as green social prescribing illustrate how built environment interventions can influence behavioural patterns at scale, particularly in relation to physical activity and mental wellbeing [3,11–13]. However, existing studies typically evaluate health and environmental outcomes separately, relying on post-hoc assessments rather than predictive modelling.

Recent work has begun to explore the integration of behavioural modelling into urban sustainability assessments, yet few studies provide an operational framework that translates behavioural change into quantifiable carbon and energy impacts. Moreover, these approaches are rarely embedded within AI-enabled decision-support systems aligned with construction and infrastructure planning processes. The CHN framework proposed in this paper builds on advances in AI-based simulation and digital infrastructure modelling to bridge this gap.

3 Methodology: Climate–Health Nexus Framework

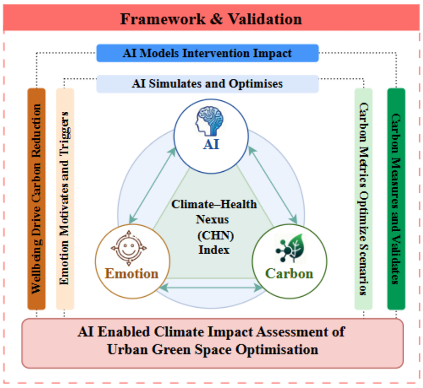

Fig. 1 CHN Framework

3.1 Framework Architecture

As illustrated in **Figure 1**, the CHN framework integrates behavioural, wellbeing and carbon dimensions within a unified simulation and optimisation architecture, enabling systematic comparison of intervention scenarios under different planning objectives.

The framework comprises three tightly coupled layers. The data layer integrates heterogeneous inputs, including anonymised NHS green social prescribing records and municipal open data describing urban form, transport and environmental conditions [3]. These datasets establish baseline behavioural patterns, contextual constraints and environmental exposure.

The modelling layer applies machine learning techniques to simulate and optimise intervention impacts. AI models capture how specific green infrastructure design features and activity-based interventions influence emotional engagement and behavioural responses, such as outdoor activity frequency, screen-time reduction and participation in community-based activities. These behavioural responses are then translated into downstream carbon and energy impacts through linked modelling pathways.

The output layer synthesises simulation results into a composite CHN Index and scenario-based performance metrics, providing decision-quality outputs for planners and infrastructure stakeholders. Importantly, the framework captures feedback loops between emotion, behaviour and carbon outcomes, enabling iterative optimisation rather than one-off, static assessment.

Formally, the CHN Index is defined as a weighted aggregation of normalised outcome indicators:

$$\mathrm{CHN} = w_b \cdot B + w_c \cdot C + w_w \cdot W$$

where B represents behavioural impact score, C and W represents the normalised carbon and energy impact score, w_b, w_c, w_w are weighting parameters reflecting planning or policy priorities, with $w_b + w_c + w_w = 1$. This formulation allows flexible comparison and optimisation of intervention scenarios under different strategic objectives, such as prioritising carbon reduction, wellbeing improvement or balanced co-benefits.

3.2 Behavioural Simulation

Behavioural responses are modelled as probabilistic changes in activity patterns triggered by specific urban interventions. Examples include increased walking frequency due to improved pedestrian infrastructure, reduced screen time associated with outdoor activity, and increased community participation through gardening initiatives. Machine learning models are trained using historical behavioural and contextual data to estimate response likelihoods across different population groups and spatial contexts, following established behavioural energy and health modelling approaches [1,2,10].

3.3 Carbon and Energy Impact Modelling

Simulated behavioural changes are mapped to carbon and energy impacts through established conversion factors and system boundaries. Reduced pharmaceutical prescribing is associated with avoided embodied and operational emissions in healthcare supply chains, consistent with NHS Net Zero accounting approaches [3]. Changes in screen time are linked to household electricity demand, while increased active travel reduces transport-related emissions. These pathways are aggregated to produce comparable carbon metrics across intervention scenarios, extending behaviour-driven energy modelling methods to the urban green infrastructure context [1].

4 Case Study: Bristol Urban Green Infrastructure

The framework is demonstrated through a case study in Bristol, UK, drawing on NHS green social prescribing records and Bristol City Council open datasets. The datasets cover a three-year period (2022–2024) and include information on prescribed activity types, locations, participation characteristics, and associated environmental attributes, alongside spatial, transport, and urban infrastructures.

Three intervention scenarios are defined to enable structured comparison of behavioural and environmental outcomes. Scenario S1 (Baseline) represents existing conditions, with no assumed change in outdoor activity, screen time, or associated carbon impacts. It serves as the reference case against which all intervention effects are evaluated. Scenario S2 (Infrastructure-focused intervention) represents a modest, environment-led strategy in which improvements to urban infrastructure, such as enhanced walking routes, improved public realm quality, and increased availability of shaded seating, encourage incremental behavioural change. Scenario S3 (Activity-focused intervention) represents a more intensive, programme-led approach centred on organised and socially facilitated activities, such as community gardening or structured group exercise. Scenario S4 (Combined intervention) integrates both infrastructure enhancements and organised activities.

AI-based models are calibrated using the local datasets to simulate behavioural responses and associated carbon and energy impacts under each intervention scenario. Behavioural responses are modelled using an interpretable supervised learning approach for tabular data (gradient-boosted decision trees), with model explanation via SHAP to support transparent scenario comparison. Model performance was evaluated using standard metrics on held-out test sets. Across behavioural prediction tasks, the models achieved consistent moderate-to-good performance (e.g., AUC values typically above 0.70 for classification tasks and low prediction error for continuous outcomes). Importantly, the modelling approach prioritises stability and consistency in relative scenario comparisons rather than individual-level predictive optimisation. The models demonstrated robust ranking of intervention scenarios and consistent directional effects, supporting their suitability for decision-support applications. Predicted behavioural changes are then mapped to carbon and energy outcomes through a transparent impact translation layer based on emissions factors and activity substitution assumptions. Training, validation, and testing use held-out data splits to ensure robustness.

4.1 Scenario-Based Simulation Results

To demonstrate the operational capability of the CHN framework, a set of representative intervention scenarios was simulated for the Bristol case study. Scenarios were designed to reflect commonly implemented urban green infrastructure measures, including (S1) baseline conditions with no additional intervention, (S2) enhanced pedestrian connectivity and shaded seating, (S3) structured green activities such as Nordic walking and community gardening, and (S4) a combined intervention integrating physical infrastructure upgrades with organised social activities. Across all scenarios, the AI models estimated probabilistic behavioural changes at the population level, including increased outdoor activity frequency, reduced average daily screen time, and increased uptake of active travel. These behavioural outputs were then translated into carbon and energy impacts using established conversion factors derived from behavioural energy, lifecycle carbon and health studies [1,3,9,10]. **Table 1** summarises the comparative results across scenarios.

Table 1. Comparative behavioural and carbon outcomes across intervention scenarios

Scenario	Change in outdoor activity (hours/week)	Change in average screen time (hours/day)	Estimated avoided emissions (kg CO_2e per capita per year)	Relative CHN Index score
S1 Baseline	0.00	0.00	0.00	0.00
S2 Infrastructure-focused	1.80	−0.35	42.00	0.46
S3 Activity-focused	2.40	−0.50	58.00	0.62
S4 Combined intervention	3.10	−0.72	81.00	0.84

The results indicate that combined interventions consistently outperform single-focus strategies. While infrastructure-only measures improve accessibility and comfort, the inclusion of organised activities amplifies behavioural engagement and downstream carbon benefits. The combined scenario (S4) yields the highest avoided emissions and overall CHN Index score, suggesting strong synergies between physical design and behavioural programming.

4.2 Interpretation of Carbon Pathways

Disaggregation of the carbon outcomes reveals that avoided pharmaceutical prescribing and reduced household electricity demand associated with lower screen time contribute a substantial share of total savings, in line with previous behaviour-driven energy studies [1]. Active travel contributes additional benefits, particularly in dense urban areas where short car trips are prevalent. These findings highlight the importance of accounting for indirect and non-obvious emission pathways when evaluating urban green infrastructure within sustainable construction and planning contexts.

4.3 Decision-Support Implications

Figure 2 illustrates the conceptual workflow of the CHN framework in general, from data integration through AI-based behavioural simulation to scenario comparison and decision-support outputs. The framework enables planners and infrastructure stakeholders to rapidly compare intervention portfolios using a unified set of metrics rather than isolated indicators. From a construction and urban planning perspective, the results demonstrate how AI-enabled simulation can support evidence-based prioritisation of green infrastructure investments aligned with sustainability, wellbeing and Net Zero objectives [1,3,4,10,14].

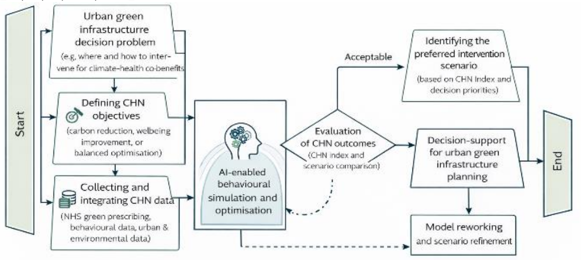

Fig 2. Overview of the AI-enabled Climate–Health Nexus (CHN) decision-support workflow.

5 Conclusions and Future Work

This paper presents an AI-enabled CHN framework that integrates behavioural modelling, carbon and energy metrics, and wellbeing indicators into a unified decision-support system for sustainable urban green infrastructure. The results demonstrate how behavioural dynamics can be operationalised through interpretable AI models to quantify indirect and system-level carbon impacts, extending conventional infrastructure assessment approaches. The case study highlights that combined infrastructure and activity-based interventions yield the strongest co-benefits across climate and health dimensions, emphasising the importance of integrating physical design with behavioural programming. From a construction and urban planning perspective, the framework provides a practical tool for scenario comparison, enabling evidence-based prioritisation of green infrastructure investments aligned with Net Zero and wellbeing objectives. Future work will focus on integration with digital twin platforms, expansion to multi-city datasets, and refinement of behavioural–carbon pathways for construction-phase and lifecycle optimisation.

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