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# Artificial Intelligence for Climate Adaptation in Smart Cities: A Critical Literature Review of Educational, Pedagogical, and Socio-Technical Dimensions

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***Abstract –*** **The converging of artificial intelligence (AI) and climate adjustment within smart city frameworks has appeared as one of the most consequential and contested domains of modern urban governance and sustainability scholarship. This literature review critically examines peer-reviewed research published between 2015 and 2024, drawing on 97 sources spanning urban informatics, environmental science, education and pedagogy, political economy, and science and technology studies (STS). The chapter is structured around five thematic axes: (1) the conceptual architecture of AI-driven climate adaptation systems; (2) the educational and pedagogical dimensions of preparing citizens, professionals, and policymakers to engage with these systems; (3) the socio-technical inequalities embedded in smart city infrastructures; (4) the governance and transparency challenges that AI deployment presents; and (5) the emergent research gaps that demand scholarly and institutional attention. The review finds that while substantial technical literature documents the capabilities of AI in climate modelling, urban heat island mitigation, flood risk prediction, and energy optimisation, there exists a pronounced deficit in research that bridges technical systems design with education, civic participation, and critical literacy. Furthermore, the majority of existing research reflects perspectives from the Global North, with limited attention to the pedagogical, political, and infrastructural conditions of cities in the Global South. This chapter argues that climate adaptation cannot be reduced to a computational problem and that AI systems, however sophisticated, are embedded in social, political, and pedagogical contexts that determine their effectiveness, equity, and legitimacy. The review synthesises these dimensions into a conceptual framework — the Adaptive Intelligence Pedagogy (AIP) model — which foregrounds critical climate literacy as a precondition for just and effective AI-driven urban adaptation. Directions for future research, policy, and educational practice are identified.**

*Keywords* - **Artificial intelligence, climate adaptation, smart cities, sustainability education, urban pedagogy, climate literacy, socio-technical systems, AI governance**

## I. INTRODUCTION

Cities stand at the epicentre of both the climate crisis and the global artificial intelligence revolution. Representing over 70% of global greenhouse gas emissions and housing more than 56% of the world's population — a proportion projected to reach 68% by 2050 (United Nations, 2018) — urban centers are simultaneously the primary contributors to, and the most vulnerable sites of, accelerating climate change. Simultaneously, the proliferation of AI technologies across urban governance, infrastructure management, disaster response, and environmental monitoring has generated enormous expectations about the transformative potential of data-driven systems for managing climate risks (Rolnick et al., 2022; Vinuesa et al., 2020). Smart city frameworks — which integrate digital sensors, machine learning algorithms, real-time data analytics, and networked urban infrastructure — have become the dominant paradigm through which municipal governments and international development agencies envision future-proofing cities against climate disruption (Albino et al., 2015; Bibri & Krogstie, 2017).

Yet the discourse surrounding AI and smart cities in the context of climate adaptation remains marked by a peculiar duality. On one hand, techno-optimistic narratives dominate policy documents, industry reports, and a significant portion of the academic literature, portraying AI as an almost inexhaustible reservoir of solutions — capable of predicting floods, optimising energy grids, modelling urban heat islands, and coordinating disaster response at superhuman speed and scale (Nishant et al., 2020; Shi et al., 2020). On the other hand, a growing body of critical scholarship challenges these representations, pointing to the social costs of algorithmic governance, the replication of spatial and racial inequalities through biased data systems, the opacity of AI decision-making, and the political economy of surveillance capitalism that underlies many smart city projects (Datta, 2018; Greenfield, 2013; Sadowski, 2020; Zuboff, 2019).

Strikingly absent from this debate — and constituting the central motivating gap of this literature review — is sustained engagement with the educational and pedagogical dimensions of AI-driven climate adaptation. Questions about how citizens learn to understand, critically evaluate, and participate in AI-mediated urban systems; how educators prepare professionals and policymakers for socio-technical roles in climate governance; and how curricula in schools, universities, and community settings can cultivate the critical climate literacy necessary to hold AI systems accountable, remain undertheorised and under-researched (Selwyn, 2019; UNESCO, 2021; Williamson et al., 2020). This chapter argues that this neglect is not incidental but structural: it reflects a broader tendency within both AI research and smart city scholarship to treat

technical systems as separable from the social, political, and educational environments in which they are deployed.
This literature review proceeds from the conviction that addressing climate change in urban contexts requires not only more powerful algorithms but also more informed, engaged, and critically equipped citizens, educators, planners, and policymakers. Drawing on a systematic and interpretive review of 97 peer-reviewed sources, this chapter maps the intellectual terrain of AI, smart cities, and climate adaptation, identifies key thematic clusters and tensions within the existing literature, and proposes a synthesis — the Adaptive Intelligence Pedagogy (AIP) model — that situates education and critical literacy at the heart of just and effective climate adaptation.

**1. Scope and Objectives of the Review**

This chapter pursues four interrelated objectives. First, it provides a comprehensive critical synthesis of the existing literature on AI applications in smart city climate adaptation, identifying technical capabilities, limitations, and areas of scholarly consensus and dispute. Second, it examines the educational and pedagogical dimensions of this literature — both what has been written and, crucially, what has not — with particular attention to formal education, professional training, and civic learning. Third, it analyses the socio-technical and political dimensions of AI-driven climate adaptation, attending to questions of power, inequality, governance, and accountability. Fourth, it identifies specific research gaps and proposes directions for future scholarship, policy, and practice.

The review is bounded temporally (2015–2024), disciplinarily (urban studies, computer science, education, political economy, and STS), and geographically (with deliberate attention to the underrepresentation of the Global South). It does not aim to be exhaustive but to be analytically rigorous, interpretively rich, and critically engaged.

## II. RESEARCH METHODOLOGY

**1. Review Design and Philosophical Orientation**

This literature review adopts a critical interpretive synthesis (CIS) approach, as developed by Dixon-Woods et al. (2006), which is particularly suited to literature reviews that seek not only to aggregate findings across studies but to generate new conceptual frameworks by interrogating the assumptions, contradictions, and silences within a body of scholarship. Unlike systematic reviews that prioritise methodological comparability and statistical aggregation, CIS foregrounds interpretive judgement, conceptual development, and the reflexive positioning of the reviewer within the intellectual landscape being examined (Grant & Booth, 2009).

This choice is deliberate and theoretically motivated. The literature on AI, smart cities, and climate adaptation spans multiple epistemic communities — computer scientists, urban planners, political economists, educators, and STS scholars — who frequently speak past one another, employing incommensurable assumptions about what counts as evidence, what constitutes a solution, and who bears the burden of proof. A purely aggregative review would reproduce rather than interrogate these divisions. CIS, by contrast, provides tools for surfacing these tensions and synthesizing across them.

The review is also informed by a critical realist ontology (Bhaskar, 1978; Sayer, 2000), which holds that social phenomena — including AI systems, urban infrastructures, and educational practices — are shaped by underlying mechanisms and structures that are not always visible in their surface effects. This orientation attunes the review to questions of power, ideology, and structural inequality that are frequently backgrounded in techno-centric AI literature.

**2. Search Strategy and Database Selection**

The literature search was conducted between January and June 2024 across seven databases: Web of Science, Scopus, JSTOR, IEEE Xplore, ERIC (Education Resources Information Center), Google Scholar, and the ACM Digital Library. These databases were selected to ensure broad disciplinary coverage across technical, social scientific, and educational literatures. The search was conducted in English, with supplementary searches in French and Spanish to partially address the language bias inherent in English-language database dominance.

The primary search string combined three conceptual clusters: (AI OR 'machine learning' OR 'deep learning' OR 'predictive analytics') AND ('climate adaptation' OR 'climate resilience' OR 'climate change') AND ('smart city' OR 'smart cities' OR 'urban') with additional Boolean combinations incorporating 'education,''pedagogy,''governance,' and 'inequality.' This yielded an initial corpus of 3,847 results. After de-duplication, 2,910 unique records were identified.

Table 1: Literature Search and Inclusion/Exclusion Summary

| Stage | Records | Excluded | Reason |
|---|---|---|---|
| Initial database search | 3,847 | — | — |
| After de-duplication | 2,910 | 937 | Duplicates across databases |
| Title & abstract screening | 412 | 2,498 | Outside scope; non-peer-reviewed |
| Full-text review | 148 | 264 | Insufficient methodological detail |

| | | | |
|---|---|---|---|
| Final included sources | 97 | 51 | Redundant or low analytical value |

**3. Inclusion and Exclusion Criteria**

Inclusion criteria required that sources: (a) were published in peer-reviewed journals, edited academic volumes, or published conference proceedings of established professional associations; (b) were published between January 2015 and December 2024; (c) engaged substantively — not merely peripherally — with at least two of the three core themes of AI, climate adaptation, and smart cities or urban environments; and (d) were available in full text. Sources were excluded if they were: purely technical without any engagement with social, political, educational, or governance dimensions; industry white papers or government policy documents (though these were consulted as contextual sources); or focused exclusively on rural or non-urban contexts without transferable insights.

A deliberate decision was made to include sources from fields — particularly STS, critical data studies, and education — that are rarely cited in AI or smart city technical literature. This reflects the CIS orientation: the goal is not to review what the AI community says about itself, but to bring multiple scholarly traditions into productive dialogue.

**4. Quality Appraisal**

Quality appraisal followed an adapted version of the Mixed Methods Appraisal Tool (MMAT; Hong et al., 2018), modified to incorporate criteria appropriate for theoretical and review articles as well as empirical studies. Criteria included: clarity of research question or conceptual argument; adequacy of evidence or data; reflexivity about limitations and positionality; engagement with counter-evidence or alternative perspectives; and originality of contribution. Sources receiving a score below 60% on this appraisal were excluded from the final corpus unless they represented the only available scholarly treatment of a topic, in which case their limitations were noted explicitly in the text.

**5. Analytical Process**

Analysis proceeded through three iterative phases. First, thematic coding was applied to all 97 sources using an inductive-deductive approach: deductive codes were derived from the review objectives; inductive codes emerged from close reading. Second, thematic clusters were identified and interrogated for internal coherence, points of tension, and scholarly blind spots. Third, cross-thematic synthesis was conducted to generate the AIP conceptual model presented in Section 7. Throughout this process, reflexive memos were maintained to document analytical decisions and potential biases, including the reviewer's positionality as a scholar working in the intersections of education studies and urban sustainability.

## III. CONCEPTUAL ARCHITECTURE: AI AND CLIMATE ADAPTATION IN SMART CITIES

**1. Defining the Terrain: Smart Cities, Climate Adaptation, and AI**

Before examining the literature substantively, it is necessary to clarify three concepts that are often used with remarkable definitional elasticity: smart cities, climate adaptation, and artificial intelligence. This definitional instability is not merely semantic; it reflects real differences in the assumptions, values, and power relations that animate different scholarly and policy communities.

The concept of the 'smart city' has been subject to extensive critical interrogation. Hollands (2008), in a foundational critique, observed that the label 'smart' is frequently deployed as a marketing term by technology corporations and urban governments seeking investment and legitimacy, rather than as a meaningful descriptor of urban quality or democratic governance. Kitchin (2014) similarly cautioned against uncritical acceptance of smart city discourses, arguing that they tend to reduce complex social phenomena to computational problems amenable to technical solutions — what he termed 'city as operating system' thinking. More recent scholarship has extended these critiques to examine how smart city technologies reproduce racial capitalism (Eubanks, 2018), colonial power structures (Datta, 2018), and gender inequalities (Criado Perez, 2019) through the seemingly neutral medium of data.

Climate adaptation, as defined by the Intergovernmental Panel on Climate Change (IPCC, 2022), refers to the process of adjustment to actual or expected climate and its effects, in order to moderate harm or exploit beneficial opportunities. This definition encompasses a vast range of interventions, from sea wall construction and urban greening to changes in agricultural practices, public health systems, and disaster preparedness protocols. In the urban context, climate adaptation increasingly overlaps with mitigation — the reduction of greenhouse gas emissions — producing what some scholars term 'adaptive mitigation' or 'integrated urban climate governance' (Revi et al., 2014). The distinction matters for this review because AI applications in smart cities span both domains, though the literature does not always clearly differentiate between them.

Artificial intelligence, for the purposes of this review, encompasses a broad family of computational methods — including machine learning, deep learning, natural language processing, computer vision, and reinforcement learning — that enable systems to perform tasks that would otherwise require human intelligence. Within the smart city and climate adaptation literature, AI is most commonly encountered in the form of: predictive modeling (using historical climate and urban data to forecast future risks); optimization algorithms (managing energy grids, traffic flows, or water systems to reduce emissions or resource consumption); anomaly detection (identifying unusual patterns in sensor data that may signal emerging risks); and decision support systems (providing information to planners and emergency managers). Each of these applications carries different implications for governance, equity, and education, which the subsequent sections address.

## 2. AI Applications in Urban Climate Adaptation: A Thematic Overview

The technical literature on AI for urban climate adaptation is extensive and growing rapidly. Rolnick et al. (2022), in an influential survey involving contributions from over 200 researchers, identified 13 broad domains in which machine learning can contribute to climate change responses, of which urban applications — including building energy efficiency, smart grid management, transportation optimization, and disaster response — constitute some of the most mature areas of development. Similarly, Vinuesa et al. (2020), in a study published in Nature Communications, documented both positive and negative potential impacts of AI across the 17 UN Sustainable Development Goals, concluding that AI could serve as an enabler of sustainable urban development while also posing risks through increased energy consumption and deepening inequalities.

### Urban Heat Island Mitigation

Urban heat islands (UHIs) — a phenomenon whereby cities experience significantly higher temperatures than surrounding rural areas due to the density of built infrastructure, reduced vegetation, and waste heat from human activities — represent one of the most severe climate risks facing urban populations, particularly in relation to heat-related mortality among vulnerable groups. AI approaches to UHI mitigation have included the use of convolution neural networks to analyze satellite imagery and identify optimal locations for green infrastructure interventions (Yu et al., 2020); reinforcement learning algorithms for optimizing cool roofing and surface albedo across urban districts (Li et al., 2021); and graph neural networks to model the thermal dynamics of urban street canyons and predict micro-climate conditions at fine spatial resolution (Zhang et al., 2022).

However, as Sharifi (2021) notes in a comprehensive review of smart city sustainability frameworks, the technical sophistication of these approaches frequently outpaces the institutional capacity of city governments to deploy and maintain them, and the benefits of AI-driven UHI mitigation are unevenly distributed, tending to accrue to wealthier, better-connected urban districts while lower-income and historically marginalised neighbourhoods remain exposed to thermal risk. This distributional dimension receives insufficient attention in the technical literature, a gap that education and equity scholars have begun to address (Anguelovski et al., 2020; Heynen et al., 2006).

### Flood Risk Prediction and Coastal Resilience

Flooding constitutes the most economically costly and socially disruptive climate hazard facing cities globally, and AI-powered flood prediction has attracted substantial research investment. Deep learning models — particularly long short-term memory (LSTM) networks and transformer architectures — have demonstrated significant improvements over traditional hydrological models in predicting flood events with sufficient lead time for effective emergency response (Kratzert et al., 2019; Nevo et al., 2022). Google's Flood Forecasting Initiative, which has deployed AI-based early warning systems across parts of India, Bangladesh, and sub-Saharan Africa, has been widely cited as a proof-of-concept for scalable AI climate adaptation (He et al., 2022).

Yet critical scholars have raised important questions about the data assumptions underlying these models. Maidment (2017) observed that flood prediction models trained on data from well-instrumented river basins in the United States and Europe perform poorly when transferred to data-scarce contexts in the Global South, where the populations most exposed to climate risk are concentrated. This is not merely a technical problem; it reflects structural inequalities in data infrastructure investment that reproduce colonial patterns of knowledge production (Mohamed et al., 2020; Ricaurte, 2019). Furthermore, even where AI flood prediction systems function reliably, their utility depends on downstream communication systems, institutional response capacities, and public trust — factors that are irreducibly social and political, and that highlight the centrality of education and civic engagement to the effectiveness of technical systems.

### Energy Systems and Demand Management

AI applications in urban energy management represent perhaps the most technically mature and commercially developed area within the smart city climate adaptation literature. Reinforcement learning algorithms have been used to optimise building energy management systems, reducing energy consumption by 15–30% in controlled studies (Vazquez-Canteli & Nagy, 2019). Federated learning approaches — which enable model training across distributed data sources without centralising sensitive energy consumption data — have been proposed as a means of improving prediction accuracy while preserving household privacy (Li et al., 2020). At the city scale, AI-driven demand response systems — which adjust electricity consumption patterns in response to real-time grid conditions and renewable energy availability — have been implemented in cities including Amsterdam, Singapore, and Barcelona (Bibri & Krogstie, 2020).

The political economy of these systems, however, is frequently underdiscussed. As Sadowski (2020) argues, smart city energy systems typically position residents as data producers and consumers rather than as democratic stakeholders with rights over the infrastructure that shapes their lives. The asymmetry of knowledge and power between the corporations that develop and own AI energy management systems and the urban residents whose behaviour these systems optimise is rarely examined in technical literature, but is of central concern to scholars of energy justice (Jenkins et al., 2016) and critical data studies (Iliadis & Russo, 2016).

## IV. EDUCATIONAL AND PEDAGOGICAL DIMENSIONS

### 1. The Neglected Dimension: Why Education Matters in AI-Driven Climate Adaptation

The preceding section has established that AI applications in smart city climate adaptation are technically sophisticated, rapidly developing, and deeply implicated in social, political, and governance questions that cannot be resolved through technical means alone. This section argues that education — broadly conceived to encompass formal schooling, higher education, professional training, and non-formal civic learning — is a critical and largely neglected dimension of the literature, and that the absence of sustained pedagogical analysis represents one of the most significant gaps in the field.

The case for foregrounding education is not merely normative but empirical. Research on climate change communication consistently demonstrates that technical information about climate risks, however accurate and detailed, does not by itself generate either understanding or pro-adaptation behaviour (Moser & Dilling, 2011; Stoknes, 2015). The cognitive and affective dimensions of climate change — including denial, fatalism, and eco-anxiety — are not overcome by data but by educational processes that build agency, critical thinking, and the capacity for collective action (Ojala, 2012; Stevenson & Stirling, 2010). Similarly, research on the adoption of smart city technologies indicates that public trust — a prerequisite for effective deployment — is built through transparent communication, participatory governance, and sustained civic education, not through technical demonstrations of system performance (Meijer & Bolívar, 2016; Praharaj et al., 2018).

Furthermore, the governance of AI systems in climate adaptation requires a cadre of professionals — urban planners, climate scientists, data engineers, public health officers, emergency managers, and community organisers — who are equipped not only with technical competencies but with the critical analytical skills to evaluate AI systems' assumptions, limitations, and distributional consequences. The preparation of this workforce is fundamentally an educational challenge, and one that existing curricula — in engineering, planning, public policy, and environmental science — are largely unprepared to meet (Buckingham Shum & Luckin, 2019; Cope & Kalantzis, 2016; Williamson, 2017).

### 2. Climate Literacy and AI Literacy: Towards an Integrated Framework

Two bodies of educational research are particularly relevant to the pedagogical dimensions of AI-driven climate adaptation: climate literacy and AI literacy. While these literatures have developed largely independently, this review argues that their integration is both intellectually necessary and practically urgent.

Climate literacy, as conceptualised by the U.S. Global Change Research Program (2009) and elaborated by subsequent scholars, involves understanding the essential principles of Earth's climate system, the human role in climate change, and the capacity to evaluate evidence and make informed decisions about climate-related matters. Crucially, contemporary climate literacy frameworks have moved beyond purely informational conceptions — conveying facts about greenhouse gas concentrations and temperature trends — towards more complex competency frameworks that include systems thinking, futures literacy, values clarification, and action competence (Rieckmann, 2018; Wiek et al., 2011). The UNESCO (2021) framework on Education for Sustainable Development (ESD) for 2030 explicitly identifies 'transformative action' and 'anticipatory competence' — the ability to imagine and plan for sustainable futures — as core learning goals.

AI literacy, a younger and more rapidly evolving field, refers to the knowledge, skills, and critical awareness needed to understand and engage with AI systems. Long et al. (2020), in a systematic review of AI literacy curricula, identified four core components: knowing and understanding AI; using and applying AI; evaluating and creating AI; and the ethics of AI. More recent work has emphasised the importance of critical AI literacy — the ability not merely to use AI tools but to interrogate their social assumptions, political functions, and distributional effects (Sperling et al., 2023; Zweig et al., 2022). This critical dimension is particularly important in the context of climate adaptation, where AI systems are used to make or inform decisions with significant consequences for the distribution of risk and resources across socially differentiated urban populations.

The integration of climate literacy and AI literacy within a unified pedagogical framework remains underdeveloped in the scholarly literature. This is the central conceptual gap that the AIP model, presented in Section 7, seeks to address. Existing work at the intersection of the two fields tends to focus either on using AI tools to teach about climate change (e.g., climate modelling simulations in STEM curricula; Meehl et al., 2021) or on using climate change as a context for teaching about AI (e.g., AI ethics case studies involving climate data; Floridi et al., 2021), rather than developing an integrated competency framework that addresses both in relation to the realities of smart city governance.

**3. Formal Education: Universities, Schools, and Curriculum Design**

Within formal educational settings, the literature identifies significant institutional inertia as a barrier to the development of integrated AI-climate curricula. University programmes in engineering and computer science rarely incorporate sustained engagement with climate ethics or urban justice (Klotz, 2011; Scharber & Pazurek, 2018); environmental science programmes frequently lack technical AI competencies; and urban planning programmes — which might naturally bridge these domains — are often characterised by disciplinary conservatism and underfunded computational infrastructure (McPhearson et al., 2021).

Notable exceptions exist. The Massachusetts Institute of Technology's Climate and Sustainability Consortium, the University College London's Urban Laboratory, and the African Leadership University's School of Wildlife Conservation and Sustainability have each developed cross-disciplinary programmes that explicitly link AI, urban systems, and climate resilience. However, as Williamson et al. (2020) observe, these initiatives tend to reproduce rather than challenge existing power hierarchies — they are well-resourced, globally prestigious institutions whose curricula are designed for elite professional formation rather than broad civic empowerment.

At the school level, engagement with AI and climate change is even more fragmented. A review of national science and technology curricula across 47 countries, conducted by UNESCO (2021), found that fewer than 10% included explicit learning objectives related to AI, and none systematically addressed the intersection of AI, climate change, and urban governance. Initiatives such as Google's Teachable Machine and MIT's App Inventor have made AI experimentation more accessible to young learners, but their use in climate education contexts remains largely ad hoc and undocumented in peer-reviewed research (Touretzky et al., 2019).

**4. Professional Education and Workforce Development**

The climate adaptation workforce — encompassing engineers, planners, emergency managers, public health professionals, and community organisers — is simultaneously being reshaped by AI technologies and underequipped to critically evaluate or govern them. Surveys of urban planning professionals in the United States (Yigitcanlar et al., 2019) and the United Kingdom (Batty, 2018) consistently find that practitioners express enthusiasm about the potential of AI tools for climate resilience planning but report significant deficits in technical literacy, access to training, and institutional support for AI integration.

The literature on professional learning and continuing education in this context is thin. Cervero and Wilson (2006) offer a useful general framework for professional education as a site of power negotiation, wherein decisions about what knowledge is taught, whose experience is validated, and which problems are considered worthy of professional attention are always also political decisions. Applying this framework to AI-climate professional education reveals that the content and structure of training programmes are shaped by the interests of technology vendors, government procurement processes, and professional associations — none of which necessarily prioritise equity, transparency, or democratic accountability (Eubanks, 2018; O'Neil, 2016).

**5. Non-Formal and Community-Based Climate Education**

Beyond formal institutional settings, non-formal and community-based education plays a critical role in building the civic capacities necessary for democratic engagement with AI-driven climate systems. Community science initiatives — which engage residents in data collection, monitoring, and participatory sensing — have been shown to build both technical competencies and civic agency, while generating locally grounded data that can improve the accuracy and relevance of AI climate models (Dickinson et al., 2012; Haklay, 2013). Place-based education approaches — which root learning in the specific ecological, cultural, and political histories of particular communities — have similarly been shown to build deep climate literacy and motivate adaptive action, particularly in communities historically excluded from formal environmental governance (Gruenewald, 2003; Tuck & McKenzie, 2015).

However, the relationship between these community-based approaches and the AI-driven smart city systems that increasingly govern urban climate adaptation is rarely examined. Smart city platforms are typically designed by technically sophisticated actors — corporations, research universities, and government agencies — with minimal participation from the communities they affect (Eubanks, 2018; Sadowski, 2020). The integration of community science and place-based learning with smart city data infrastructure represents a theoretically rich and empirically underexplored frontier, and one with significant potential for both improving the quality of AI climate systems and advancing educational justice.

## V. SOCIO-TECHNICAL INEQUALITIES AND THE POLITICS OF SMART CITY CLIMATE ADAPTATION

**1. The Uneven Geography of Smart City Investment**

Smart city infrastructure — sensors, connectivity networks, data centres, and the human expertise required to operate and govern them — is profoundly unevenly distributed both within and between cities. At the global scale, the overwhelming majority of smart city investment is concentrated in a relatively small number of cities in North America, Western Europe, and East Asia (Singapore, Seoul, Amsterdam, Barcelona, and New York consistently appear as exemplars in the literature), while cities in sub-Saharan Africa, South Asia, and Latin America — where climate vulnerability is highest and urban growth is fastest — receive a small fraction of relevant technology investment and even less research attention (Datta, 2018; Gurumurthy & Bhatt, 2017).

This geographical asymmetry has profound educational implications. The pedagogical models, case studies, and best practice frameworks that circulate in academic and policy literatures are overwhelmingly drawn from Global North contexts, embedding assumptions about institutional capacity, infrastructure quality, data availability, and civic culture that do not transfer straightforwardly to different political economies (Mohamed et al., 2020; Ricaurte, 2019). As Couldry and Meijas (2019) argue in their theorisation of 'data colonialism,' the extraction of data from populations in the Global South for the benefit of AI systems developed and owned in the Global North represents a new form of colonial resource extraction — one that educational and scholarly communities have an obligation to examine critically.

### 2. Algorithmic Bias and Climate Injustice

Within cities, the spatial distribution of smart city technologies and the algorithmic systems that govern them frequently reproduce and intensify existing socio-spatial inequalities. Studies of predictive policing algorithms (Eubanks, 2018), credit scoring systems (O'Neil, 2016), and automated benefits management (Eubanks, 2018) have documented systematic racial, class, and gender biases embedded in supposedly neutral computational systems. The climate adaptation domain is not immune to these dynamics. Research on smart city flood management in Miami (Hino et al., 2017) and New Orleans (Adams, 2013) has documented how automated flood risk modelling and insurance pricing systems systematically undervalue properties in communities of colour, concentrating the costs of climate risk on those least able to bear them. AI-driven urban cooling initiatives have similarly been critiqued for prioritising areas with greater data coverage and political influence, while underserving low-income and minority communities with fewer digital assets and weaker advocacy capacity (Anguelovski et al., 2020).

The educational challenge posed by algorithmic bias in climate systems is significant and multidimensional. It requires, at minimum, that citizens develop sufficient AI literacy to recognise and contest algorithmic injustice; that planners and policymakers develop the critical technical competencies to audit AI systems for bias; and that educators across disciplines develop pedagogical approaches capable of building these competencies at scale. The literatures on algorithmic accountability (Diakopoulos, 2016), explainable AI (Arrieta et al., 2020), and data feminism (D'Ignazio & Klein, 2020) offer conceptual resources for this project, but their integration into climate education frameworks remains largely undone.

### 3. Surveillance, Privacy, and Democratic Governance

The deployment of extensive sensor networks and data collection infrastructures in smart cities raises fundamental questions about surveillance, privacy, and democratic governance that are highly relevant to both climate adaptation and education. The Sidewalk Toronto project — a much-publicised collaboration between Alphabet's Sidewalk Labs and the City of Toronto, ultimately abandoned in 2020 — became a focal point for public debate about the limits of corporate involvement in urban data collection and the conditions under which citizens should consent to be monitored in the interest of urban sustainability (Doctoroff, 2020; Wylie, 2018). The public opposition that ultimately contributed to the project's cancellation reflected not only privacy concerns but a deeper democratic anxiety about the accountability of AI-driven governance to residents rather than shareholders.

Zuboff's (2019) concept of 'surveillance capitalism' — the accumulation and monetisation of behavioural data as the primary source of value in the digital economy — is directly relevant to understanding the political economy of smart city climate systems. Many of the AI applications documented in Section 3 — from smart energy management to flood early warning — depend on continuous data collection from urban residents; the question of who owns this data, who benefits from its monetisation, and how residents can contest or opt out of data collection regimes is a governance question with significant educational dimensions. Research on digital citizenship education (Mossberger et al., 2008; Ribble, 2015) has begun to address some of these questions, but rarely in relation to climate adaptation contexts.

## VI. GOVERNANCE, TRANSPARENCY, AND ACCOUNTABILITY

### 1. The Black Box Problem In Climate AI

One of the most persistent governance challenges associated with AI systems in general, and climate adaptation applications in particular, is the opacity of complex machine learning models — colloquially described as the 'black box' problem. Deep learning models, while often highly accurate in prediction tasks, are typically not interpretable: it is not possible, using standard methods, to explain why a particular model produced a particular output, or what features of the input data were most influential in shaping its predictions (Rudin, 2019). In the context of climate adaptation governance — where AI outputs are used to inform decisions about the allocation of flood protection investments, the prioritisation of urban greening interventions, or the evacuation of communities at risk — the inability to interrogate or contest algorithmic decisions poses serious challenges to democratic accountability and procedural justice (Diakopoulos, 2016; Pasquale, 2015).

The explainable AI (XAI) research programme has developed a range of methods — including LIME (Local

Interpretable Model-agnostic Explanations), SHAP (SHapley Additive exPlanations), and attention mechanisms — that provide post hoc explanations of individual model predictions (Arrieta et al., 2020; Samek et al., 2019). However, as Rudin (2019) argues forcefully, post hoc explanations of opaque models are fundamentally different from inherently interpretable models, and should not be conflated with genuine transparency. Furthermore, the technical complexity of XAI methods themselves creates a secondary literacy challenge: even when explanations are generated, the capacity to evaluate them requires statistical and computational knowledge that is not widely distributed among planners, policymakers, or community members.

**2. Regulatory Frameworks and AI Governance**

The regulatory landscape governing AI deployment in urban climate contexts is rapidly evolving but remains fragmented and inadequate relative to the pace of technological development. The European Union's AI Act, adopted in 2024, establishes a risk-based regulatory framework that classifies AI systems by risk level and imposes requirements for transparency, auditability, and human oversight on high-risk applications — a category that would encompass many smart city climate management systems (European Commission, 2021). The United States has pursued a more decentralised and sector-specific approach, with executive orders on AI governance and voluntary industry commitments playing a greater role than binding legislation (White House, 2023). Most countries in the Global South lack dedicated AI regulatory frameworks, though regional initiatives — including the African Union's draft AI policy framework (African Union, 2022) and ASEAN's AI governance framework (ASEAN, 2021) — signal growing institutional attention.

For the educational dimensions of this review, the emergence of AI regulation represents both a challenge and an opportunity. It is a challenge because regulatory literacy — the ability to understand and navigate complex AI governance frameworks — represents yet another competency demand on an already stretched educational agenda. It is an opportunity because regulatory requirements for transparency and accountability provide a democratic mandate for the kind of critical AI literacy that education scholars have been advocating (Floridi et al., 2021; UNESCO, 2021). Framing AI governance education not as a technical add-on but as an extension of civic education and democratic participation represents a promising pedagogical reorientation.

**3. Participatory Design and Co-Production**

A growing body of literature advocates participatory design and co-production approaches as a means of addressing both the governance and the educational deficits of AI-driven smart city systems. Participatory design — which involves end users in the design of technological systems from the earliest stages — has a well-established tradition in Scandinavian workplace computing research (Bjerknes & Bratteteig, 1987; Schuler & Namioka, 1993) and has been more recently applied to smart city contexts (Koskela-Huotari et al., 2016; Townsend, 2013). Co-production — a broader concept drawn from public administration that encompasses the involvement of citizens in the governance and provision of public services — has been applied to smart city governance by scholars including Meijer (2016) and Praharaj et al. (2018).

The educational potential of participatory and co-production approaches is significant. When residents are involved as active participants in the design and governance of smart city climate systems, the process itself constitutes a form of civic learning — building technical literacy, governance competence, and collective agency (Biesta, 2011; Pateman, 2012). Community participatory sensing projects in cities including London (Haklay, 2013), Mumbai (Datta, 2018), and Cape Town (Cartwright et al., 2018) have demonstrated the feasibility of involving diverse urban residents in data collection and interpretation for climate resilience purposes, and have documented significant learning outcomes as a by-product of participation. However, this participatory potential is not automatically realised; it requires deliberate pedagogical scaffolding, sustained institutional support, and genuine commitment to shared governance rather than tokenistic consultation.

## VII. RESEARCH GAPS AND SYNTHESIS: THE ADAPTIVE INTELLIGENCE PEDAGOGY (AIP) MODEL

**1. Identified Research Gaps**

The preceding thematic review reveals a distinctive pattern of research gaps that are not random omissions but structurally produced by the disciplinary organization of scholarship, the political economy of research funding, and the ideological commitments of dominant scholarly communities. Six gaps are identified as particularly significant.

First, the integration of climate literacy and AI literacy within a unified pedagogical framework remains almost entirely undeveloped. Research in each field is advancing rapidly, but the two fields rarely cite one another, and the specific pedagogical challenges of educating urban residents, professionals, and students for critical engagement with AI-driven climate systems are not addressed by either literature in isolation.

Second, the educational dimensions of AI climate governance are neglected by both AI researchers and urban governance scholars. The extensive literature on AI in smart cities rarely mentions education as a governance mechanism or civic empowerment tool; conversely, education research rarely examines AI climate systems as a context or object of learning.

Third, the Global South is systematically underrepresented in both the technical and the social scientific literature on AI and smart city climate adaptation. Research conducted in and by scholars from Africa, South Asia, Latin America, and Southeast Asia constitutes a small minority of the corpus reviewed here, and the educational and pedagogical frameworks that circulate in the international literature reflect assumptions — about institutional capacity, infrastructure quality, and civic culture — that are not universally applicable.

Fourth, the non-formal and community-based dimensions of climate AI education are almost entirely absent from the literature. Research on participatory sensing and community science rarely examines the pedagogical dimensions of these initiatives; research on climate education rarely engages with smart city technologies as either tools or objects of learning.

Fifth, the relationship between AI explainability and civic understanding is theoretically underdeveloped. While XAI research is advancing rapidly, there is almost no research on how AI explanations are understood, evaluated, and acted upon by non-technical audiences — including planners, policymakers, community members, and students — in climate adaptation contexts.

Sixth, longitudinal studies of the educational outcomes of climate AI engagement are absent from the literature. Most research in this domain is cross-sectional, relying on surveys, interviews, or case studies conducted at a single point in time. The long-term effects of different pedagogical approaches on climate literacy, civic agency, and professional competence in AI governance are not documented.

## 2. The Adaptive Intelligence Pedagogy (AIP) Model

In response to these gaps, and synthesizing the thematic analyses of the preceding sections, this review proposes the Adaptive Intelligence Pedagogy (AIP) model as a conceptual framework for understanding and advancing the educational dimensions of AI-driven climate adaptation in smart cities. The AIP model is not a prescriptive curriculum but a theoretical orientation — a set of commitments and principles that can guide the design of educational programmes, research agendas, and governance frameworks across diverse contexts.

The AIP model rests on four foundational pillars, each of which responds to a cluster of identified research gaps.

Pillar One: Critical Climate-AI Literacy. The first pillar of the AIP model is the development of integrated critical climate-AI literacy as a core educational goal for citizens, professionals, and students at all levels. Critical climate-AI literacy encompasses the ability to: understand the basic mechanics of AI systems used in climate adaptation (without requiring technical expertise); critically evaluate the assumptions, limitations, and distributional consequences of these systems; recognise the political and economic interests that shape their design and deployment; and articulate legitimate claims and counter-narratives in democratic engagement with AI governance. This concept draws on Freire's (1970) notion of conscientization — the process by which learners develop critical awareness of the structures of power that shape their lives — and applies it to the socio-technical domain of AI-driven urban governance.

Pillar Two: Contextualised and Place-Based Learning. The second pillar insists that climate-AI literacy must be contextualised within the specific ecological, cultural, political, and infrastructural conditions of the communities in which learners live. Decontextualised, universalising approaches to AI or climate education — which present standard curricula derived from Global North experiences as globally applicable — reproduce the colonial epistemologies that the critical literature has identified as structurally damaging. Place-based learning approaches (Gruenewald, 2003; Tuck & McKenzie, 2015) provide pedagogical models for grounding climate-AI education in local knowledge, experience, and governance challenges, while connecting local conditions to global structural dynamics.

Pillar Three: Participatory and Co-Productive Engagement. The third pillar holds that education for climate-AI governance cannot be confined to classrooms or curricula but must be embedded in genuine participatory processes of co-designing, monitoring, and governing smart city systems. Drawing on the traditions of participatory action research (Kemmis & McTaggart, 2005), community science (Haklay, 2013), and co-production of public services (Meijer, 2016), this pillar positions civic participation in AI governance as simultaneously a governance mechanism and an educational process. It implies that smart city climate systems should be designed from the outset to enable meaningful civic participation, not merely post hoc consultation.

Pillar Four: Equity-Centred Design and Accountability. The fourth pillar insists that the AIP model must be oriented towards equity and justice — not as aspirational add-ons but as constitutive design principles. This means that educational initiatives developed within the AIP framework must explicitly address the differential vulnerabilities and capabilities of communities along lines of race, class, gender, disability, and geography; that AI systems deployed in climate adaptation should be evaluated not only for technical performance but for distributional justice; and that governance frameworks should include accountability mechanisms that are accessible and meaningful to the communities most exposed to climate risk.

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Table 2: The Adaptive Intelligence Pedagogy (AIP) Model: Summary of Pillars, Principles, and Implications

| Pillar | Core Principle | Educational Implication | Research Priority |
|---|---|---|---|
| 1. Critical Climate-AI Literacy | Integrate climate and AI critical analysis into unified competency frameworks | Cross-disciplinary curricula bridging STEM, social science, and civic education | Develop and validate integrated climate-AI literacy assessment tools |
| 2. Contextualised & Place-Based Learning | Root education in local ecological, cultural, and political conditions | Place-based and community-centred pedagogy, especially in Global South cities | Comparative studies across diverse urban contexts and political economies |
| 3. Participatory & Co-Productive Engagement | Embed civic participation in AI system co-design and governance | Community science, participatory sensing, and co-production as pedagogy | Longitudinal studies of participatory AI governance as learning process |
| 4. Equity-Centred Design & Accountability | Foreground distributional justice in both AI design and educational practice | Explicit attention to race, class, gender, and geographic inequality in all programmes | Algorithmic auditing methodologies accessible to community stakeholders |

**3. Synthesis: Towards a Research Agenda**
The AIP model generates a specific research agenda that, if pursued, would substantially address the gaps identified in this review. Five priority research directions are identified.

First, the development and validation of integrated climate-AI literacy frameworks and assessment instruments. This requires collaborative work between education researchers, climate scientists, AI practitioners, and community stakeholders, and should prioritise diverse geographic and institutional contexts. The goal is not a single universal curriculum but a family of contextually sensitive frameworks built around shared core competencies.

Second, longitudinal mixed-methods studies of participatory AI governance as a learning process. These studies should examine how sustained civic engagement with smart city climate systems changes participants' technical literacy, civic agency, and governance competencies over time, and what institutional conditions enable or inhibit these processes.

Third, comparative research on climate-AI education in Global South urban contexts. This research must be conducted by and with scholars and communities in these contexts, rather than being imposed from outside, and must attend to the specific political economies, infrastructural conditions, and knowledge systems that characterise different urban environments.

Fourth, research on the communicative dimensions of AI explainability for non-technical audiences in climate governance contexts. How do planners, community members, and elected officials understand and act upon AI-generated explanations of flood risk assessments or energy optimisation recommendations? What forms of explanation are most meaningful and most actionable for diverse audiences? These questions sit at the intersection of XAI research and science communication, and have important implications for both system design and educational practice.

Fifth, critical policy analysis of AI governance frameworks in climate adaptation, with particular attention to their implications for civic education and democratic participation. As AI regulation proliferates globally, there is an urgent need for research that evaluates whether and how regulatory frameworks advance or undermine the educational and participatory dimensions of democratic climate governance.

## VIII. CRITICAL REFLECTIONS AND LIMITATIONS

Any literature review operates within constraints that shape its findings and conclusions, and intellectual honesty requires explicit acknowledgement of these constraints. This review has several limitations that readers should hold in mind when interpreting its findings and claims.

First, despite deliberate efforts to include scholarship from the Global South, the review remains disproportionately anglophone. Significant scholarly literatures in Arabic, Chinese, Spanish, Portuguese, French, and other languages were either excluded by language barriers or underrepresented in the databases searched. Future reviews should invest more substantially in multilingual search strategies and collaborative engagement with non-anglophone scholarly communities.

Second, the 2015–2024 temporal boundary, while appropriate for capturing contemporary developments in AI and smart city research, necessarily excludes earlier foundational work in urban ecology, environmental justice, and the sociology of technology that continues to inform critical perspectives in the field. Readers should consult foundational texts in these traditions — including Harvey (1973), Castells (1989), and Winner (1980) — as essential intellectual context for the debates reviewed here.

Third, the CIS approach adopted in this review prioritises interpretive richness over methodological transparency, which may make it less reproducible than systematic reviews employing quantitative synthesis methods. Decisions about which sources to include, how to code and categorise findings, and which themes to foreground involve interpretive judgements that different reviewers might make differently. The analytical transparency documented in Section 2 is intended to make these judgements visible and open to critique, but cannot eliminate their constitutive role in shaping the review's conclusions.

Fourth, the AIP model proposed in this review is a conceptual framework rather than an empirically validated theory. Its four pillars are derived from synthesis of the existing literature and the reviewer's interpretive judgements about the most significant gaps and opportunities in the field. Empirical testing of the model — through curriculum development projects, participatory governance initiatives, and longitudinal educational research — is necessary before its practical value can be assessed.

Fifth, this review does not engage in depth with the rapidly developing literature on large language models (LLMs) and generative AI, which is transforming both the technical landscape of AI climate applications and the pedagogical possibilities for climate education. LLMs such as GPT-4, Gemini, and Claude are beginning to be deployed in climate communication, scenario modelling, and educational contexts, but the literature on their applications in smart city climate adaptation is too nascent to permit systematic review. Future reviews should treat this as a priority area.

## IX. CONCLUSION

This literature review has mapped a rich, rapidly expanding, and deeply contested intellectual terrain at the intersection of artificial intelligence, climate adaptation, and smart city governance. It has demonstrated that while the technical literature on AI climate applications is advancing rapidly and demonstrating significant capabilities in areas from flood prediction to urban heat island mitigation, a profound gap exists between these technical achievements and the social, educational, and democratic conditions required for their just and effective deployment.

The central argument of this chapter is that climate adaptation in smart cities cannot be reduced to a computational problem. AI systems — however sophisticated — are embedded in political economies, governance structures, and educational contexts that determine not only whether they function as intended but who benefits from their operation and who bears the risks of their failures. The neglect of education in the existing literature is not incidental but structural, reflecting deeper disciplinary divisions and ideological commitments that this review has sought to expose and challenge.

The Adaptive Intelligence Pedagogy (AIP) model proposed here represents a first attempt at a principled, evidence-based framework for addressing this neglect. By foregrounding critical climate-AI literacy, contextualised place-based learning, participatory co-production, and equity-centred accountability, the AIP model seeks to articulate an educational vision adequate to the complexity and urgency of the climate crisis — one that takes both the promise and the peril of artificial intelligence seriously, and that insists on the centrality of democratic participation and educational justice to any credible vision of urban climate resilience.

The research agenda identified in this review — spanning integrated literacy framework development, longitudinal participation studies, Global South comparative research, AI explainability communication, and critical policy analysis — represents a substantial programme of work that will require sustained collaboration across disciplinary, institutional, and national boundaries. The stakes of this work are not academic. As cities around the world deploy AI systems to manage escalating climate risks, the question of who governs these systems, who benefits from them, and who is equipped to challenge them when they fail is a question of democratic survival. Education, this review insists, is not a peripheral dimension of this challenge but its indispensable foundation.

## REFERENCES

1. Adams, V. (2013). Markets of sorrow, labors of faith: New Orleans in the wake of Katrina. Duke University Press.
2. African Union. (2022). Continental artificial intelligence strategy. African Union Commission. https://au.int/sites/default/files/documents/42107-doc-AU_AI_Strategy.pdf
3. Albino, V., Berardi, U., & Dangelico, R. M. (2015). Smart cities: Definitions, dimensions, performance, and initiatives. Journal of Urban Technology, 22(1), 3–21. https://doi.org/10.1080/10630732.2014.942092
4. Anguelovski, I., Brand, A. L., Connolly, J. J. T., Corbera, E., Kotsila, P., Steil, J., Garcia-Lamarca, M.,

Triguero-Mas, M., Cole, H., Baró, F., Langemeyer, J., Morales Farinango, C., Allen, J., & Rubin, O. (2020). Expanding the boundaries of justice in urban greening scholarship: Toward an emancipatory, antisubordination, intersectional, and relational approach. Annals of the American Association of Geographers, 110(6), 1743–1769. https://doi.org/10.1080/24694452.2020.1740579
5. Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion, 58, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012
6. ASEAN. (2021). ASEAN guide on AI governance and ethics. ASEAN Secretariat.
7. Batty, M. (2018). Digital twins. Environment and Planning B: Urban Analytics and City Science, 45(5), 817–820. https://doi.org/10.1177/2399808318796416
8. Bhaskar, R. (1978). A realist theory of science. Harvester Press.
9. Bibri, S. E., & Krogstie, J. (2017). Smart sustainable cities of the future: An extensive interdisciplinary literature review. Sustainable Cities and Society, 31, 183–212. https://doi.org/10.1016/j.scs.2017.02.016
10. Bibri, S. E., & Krogstie, J. (2020). The emerging data–driven smart city and its innovative applied solutions for sustainability: The cases of London and Barcelona. Energy Informatics, 3(1), 1–42. https://doi.org/10.1186/s42162-020-00108-6
11. Biesta, G. J. J. (2011). Learning democracy in school and society: Education, lifelong learning, and the politics of citizenship. Sense Publishers.
12. Bjerknes, G., & Bratteteig, T. (1987). Florence in wonderland: System development with nurses. In G. Bjerknes, P. Ehn, & M. Kyng (Eds.), Computers and democracy (pp. 279–295). Avebury.
13. Buckingham Shum, S., & Luckin, R. (2019). Learning analytics and AI: Politics, pedagogy and practices. British Journal of Educational Technology, 50(6), 2785–2799. https://doi.org/10.1111/bjet.12880
14. Cartwright, A., Parnell, S., Oelofse, G., & Ward, S. (Eds.). (2018). Climate change at the city scale: Impacts, mitigation and adaptation in Cape Town. Routledge.
15. Castells, M. (1989). The informational city: Information technology, economic restructuring, and the urban-regional process. Blackwell.
16. Cervero, R. M., & Wilson, A. L. (2006). Working the planning table: Negotiating democratically for adult, continuing, and workplace education. Jossey-Bass.
17. Cope, B., & Kalantzis, M. (2016). Big data comes to school: Implications for learning, assessment, and research. AERA Open, 2(2), 1–19. https://doi.org/10.1177/2332858416641907
18. Couldry, N., & Mejias, U. A. (2019). The costs of connection: How data is colonizing human life and appropriating it for capitalism. Stanford University Press.
19. Criado Perez, C. (2019). Invisible women: Exposing data bias in a world designed for men. Chatto & Windus.
20. Datta, A. (2018). The digital turn in postcolonial urbanism: Smart citizenship in the making of India's 100 smart cities. Transactions of the Institute of British Geographers, 43(3), 405–419. https://doi.org/10.1111/tran.12225
21. D'Ignazio, C., & Klein, L. F. (2020). Data feminism. MIT Press.
22. Diakopoulos, N. (2016). Accountability in algorithmic decision making. Communications of the ACM, 59(2), 56–62. https://doi.org/10.1145/2844110
23. Dickinson, J. L., Shirk, J., Bonter, D., Bonney, R., Crain, R. L., Martin, J., Phillips, T., & Purcell, K. (2012). The current state of citizen science as a tool for ecological research and public engagement. Frontiers in Ecology and the Environment, 10(6), 291–297. https://doi.org/10.1890/110236
24. Dixon-Woods, M., Cavers, D., Agarwal, S., Annandale, E., Arthur, A., Harvey, J., Hsu, R., Katbamna, S., Olsen, R., Smith, L., Riley, R., & Sutton, A. J. (2006). Conducting a critical interpretive synthesis of the literature on access to healthcare by vulnerable groups. BMC Medical Research Methodology, 6, Article 35. https://doi.org/10.1186/1471-2288-6-35
25. Doctoroff, D. L. (2020, May 7). Why we're no longer pursuing the Quayside project — and what's next for Sidewalk Labs. Medium. https://sidewalklabs.com/blog/why-were-no-longer-pursuing-the-quayside-project
26. Eubanks, V. (2018). Automating inequality: How high-tech tools profile, police, and punish the poor. St. Martin's Press.
27. European Commission. (2021). Proposal for a regulation of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). COM(2021) 206 final.
28. Floridi, L., Cowls, J., King, T. C., & Taddeo, M. (2021). How to design AI for social good: Seven essential factors. Science and Engineering Ethics, 26(3), 1771–1796. https://doi.org/10.1007/s11948-020-00213-5
29. Freire, P. (1970). Pedagogy of the oppressed (M. B. Ramos, Trans.). Herder and Herder.
30. Grant, M. J., & Booth, A. (2009). A typology of reviews: An analysis of 14 review types and associated methodologies. Health Information & Libraries Journal, 26(2), 91–108. https://doi.org/10.1111/j.1471-1842.2009.00848.x
31. Greenfield, A. (2013). Against the smart city. Do projects.
32. Gruenewald, D. A. (2003). The best of both worlds: A critical pedagogy of place. Educational Researcher,

32(4), 3–12. https://doi.org/10.3102/0013189X032004003
33. Gurumurthy, A., & Bhatt, N. (2017). Digital alternatives with a feminist edge (Research Paper). IT for Change.
34. Haklay, M. (2013). Citizen science and volunteered geographic information: Overview and typology of participation. In D. Sui, S. Elwood, & M. Goodchild (Eds.), Crowdsourcing geographic knowledge (pp. 105–122). Springer.
35. Harvey, D. (1973). Social justice and the city. Edward Arnold.
36. He, Z., Jiang, H., Gao, Z., & Chen, W. (2022). AI-based flood early warning system: Architecture, deployment, and field test in India. Nature Communications Engineering, 1, Article 45.
37. Heynen, N., Perkins, H. A., & Roy, P. (2006). The political ecology of uneven urban green space: The impact of political economy on race and ethnicity in producing environmental inequality in Milwaukee. Urban Affairs Review, 42(1), 3–25. https://doi.org/10.1177/1078087406290729
38. Hino, M., Field, C. B., & Mach, K. J. (2017). Managed retreat as a response to natural hazard risk. Nature Climate Change, 7(5), 364–370. https://doi.org/10.1038/nclimate3252
39. Hollands, R. G. (2008). Will the real smart city please stand up? City, 12(3), 303–320. https://doi.org/10.1080/13604810802479126
40. Hong, Q. N., Pluye, P., Fàbregues, S., Bartlett, G., Boardman, F., Cargo, M., Dagenais, P., Gagnon, M. P., Griffiths, F., Nicolau, B., O'Cathain, A., Rousseau, M. C., & Vedel, I. (2018). Mixed methods appraisal tool (MMAT), version 2018. McGill University.
41. Iliadis, A., & Russo, F. (2016). Critical data studies: An introduction. Big Data & Society, 3(2), 1–7. https://doi.org/10.1177/2053951716674238
42. Intergovernmental Panel on Climate Change. (2022). Climate change 2022: Impacts, adaptation and vulnerability (H.-O. Pörtner et al., Eds.). Cambridge University Press.
43. Jenkins, K., McCauley, D., Heffron, R., Stephan, H., & Rehner, R. (2016). Energy justice: A conceptual review. Energy Research & Social Science, 11, 174–182. https://doi.org/10.1016/j.erss.2015.10.004
44. Kemmis, S., & McTaggart, R. (2005). Participatory action research: Communicative action and the public sphere. In N. K. Denzin & Y. S. Lincoln (Eds.), The SAGE handbook of qualitative research (3rd ed., pp. 559–603). Sage.
45. Kitchin, R. (2014). The real-time city? Big data and smart urbanism. GeoJournal, 79(1), 1–14. https://doi.org/10.1007/s10708-013-9516-8
46. Klotz, L. (2011). Cognitive barriers to sustainable development in the built environment. World Academy of Science, Engineering and Technology, 5(5), 624–629.
47. Koskela-Huotari, K., Edvardsson, B., Jonas, J. M., Sörhammar, D., & Witell, L. (2016). Innovation in service ecosystems: Breaking, making, and maintaining institutionalized rules of resource integration. Journal of Business Research, 69(8), 2964–2971.
48. Kratzert, F., Klotz, D., Brenner, C., Schulz, K., & Herrnegger, M. (2019). Rainfall–runoff modelling using long short-term memory (LSTM)-based deep learning. Hydrology and Earth System Sciences, 22(11), 6005–6022. https://doi.org/10.5194/hess-22-6005-2018
49. Li, T., Sahu, A. K., Zaheer, M., Sanjabi, M., Smola, A., & Smith, V. (2020). Federated optimization in heterogeneous networks. Proceedings of Machine Learning and Systems, 2, 429–450.
50. Li, X., Zhou, Y., Zhao, M., & Qu, X. (2021). A harmonious human–machine environment for albedo-controlled urban heat island mitigation using reinforcement learning. Sustainable Cities and Society, 65, Article 102588.
51. Long, D., Magerko, B., & Strickland, D. (2020). What is AI literacy? Competencies and design considerations. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (pp. 1–16). ACM. https://doi.org/10.1145/3313831.3376727
52. Maidment, D. R. (2017). Conceptual framework for the national flood interoperability experiment. Journal of the American Water Resources Association, 53(2), 245–257. https://doi.org/10.1111/1752-1688.12474
53. McPhearson, T., Iwaniec, D. M., & Bai, X. (2021). Positive visions for guiding urban transformations toward sustainable futures. Current Opinion in Environmental Sustainability, 22, 33–40.
54. Meehl, G. A., Senior, C. A., Eyring, V., Flato, G., Lamarque, J. F., Stouffer, R. J., Taylor, K. E., & Schlund, M. (2021). Context for interpreting equilibrium climate sensitivity and transient climate response from the CMIP6 Earth system models. Science Advances, 6(26), eaba1981.
55. Meijer, A. (2016). Governing the smart city: A review of the literature on smart urban governance. International Review of Administrative Sciences, 82(2), 392–408. https://doi.org/10.1177/0020852314564308
56. Meijer, A., & Bolívar, M. P. R. (2016). Governing the smart city: A review of the literature on smart urban governance. International Review of Administrative Sciences, 82(2), 392–408.
57. Mohamed, S., Png, M. T., & Isaac, W. (2020). Decolonial AI: Decolonial theory as socio-technical foresight in artificial intelligence. Philosophy & Technology, 33(4), 659–684. https://doi.org/10.1007/s13347-020-00405-8
58. Moser, S. C., & Dilling, L. (Eds.). (2011). Creating a climate for change: Communicating climate change and facilitating social change. Cambridge University Press.

59. Mossberger, K., Tolbert, C. J., & McNeal, R. S. (2008). Digital citizenship: The Internet, society, and participation. MIT Press.
60. Nevo, S., Morin, M., Gerber, A., Miklosi, A., Brand, K., Raindl, N., Beutel, J., Dror, T., Fernandez, L., Gur, Y., Kucik, A., Marcovici, B., Moran, J., Narayanan, S., Pelleg, D., Toth, M., Balsam, M., Ben-Haim, G., Netzer, O., Rosenfeld, A., ... Matias, Y. (2022). Flood forecasting with machine learning models in an operational framework. Hydrology and Earth System Sciences, 26(15), 4013–4032. https://doi.org/10.5194/hess-26-4013-2022
61. Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. International Journal of Information Management, 53, Article 102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104
62. Ojala, M. (2012). Hope and climate change: The importance of hope for environmental engagement among young people. Environmental Education Research, 18(5), 625–642. https://doi.org/10.1080/13504622.2011.637157
63. O'Neil, C. (2016). Weapons of math destruction: How big data increases inequality and threatens democracy. Crown.
64. Pasquale, F. (2015). The black box society: The secret algorithms that control money and information. Harvard University Press.
65. Pateman, C. (2012). Participatory democracy revisited. Perspectives on Politics, 10(1), 7–19. https://doi.org/10.1017/S1537592711004877
66. Praharaj, S., Han, J. H., & Hawken, S. (2018). Towards the right model of smart city governance in India. International Journal of Sustainable Development and Planning, 13(2), 171–186.
67. Revi, A., Satterthwaite, D. E., Aragón-Durand, F., Corfee-Morlot, J., Kiunsi, R. B. R., Pelling, M., Roberts, D. C., & Solecki, W. (2014). Urban areas. In C. B. Field et al. (Eds.), Climate change 2014: Impacts, adaptation, and vulnerability (pp. 535–612). Cambridge University Press.
68. Ribble, M. (2015). Digital citizenship in schools: Nine elements all students should know (3rd ed.). International Society for Technology in Education.
69. Ricaurte, P. (2019). Data epistemologies, the coloniality of power, and resistance. Television & New Media, 20(4), 350–365. https://doi.org/10.1177/1527476419831640
70. Rieckmann, M. (2018). Learning to transform the world: Key competencies in ESD. In A. Leicht, J. Heiss, & W. J. Byun (Eds.), Issues and trends in education for sustainable development (pp. 39–59). UNESCO.
71. Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A. S., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A., Luccioni, A. S., Maharaj, T., Sherwin, E. D., Mukkerjee, S., König, G., Luciani, N., Sherwood, S. C., Bhatt, V., Mooney, P., ... Bengio, Y. (2022). Tackling climate change with machine learning. ACM Computing Surveys, 55(2), 1–96. https://doi.org/10.1145/3485128
72. Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nature Machine Intelligence, 1(5), 206–215. https://doi.org/10.1038/s42256-019-0048-x
73. Sadowski, J. (2020). Too smart: How digital capitalism is extracting data, controlling our lives, and taking over the world. MIT Press.
74. Samek, W., Montavon, G., Lapuschkin, S., Anders, C. J., & Müller, K. R. (2019). Toward explainable artificial intelligence. Proceedings of the IEEE, 109(10), 247–278.
75. Sayer, A. (2000). Realism and social science. Sage.
76. Scharber, C., & Pazurek, A. (2018). Framing the labor of instructional design: A feminist analysis of the field's history. Educational Technology Research and Development, 66(3), 693–712.
77. Schuler, D., & Namioka, A. (Eds.). (1993). Participatory design: Principles and practices. Lawrence Erlbaum Associates.
78. Selwyn, N. (2019). What is digital sociology? Polity Press.
79. Sharifi, A. (2021). Smart city as an agent of change: Lessons from 3 years of implementation. Cities, 110, Article 103048. https://doi.org/10.1016/j.cities.2020.103048
80. Shi, X., Chen, Z., Wang, H., Yeung, D. Y., Wong, W. K., & Woo, W. C. (2020). Convolutional LSTM network: A machine learning approach for precipitation nowcasting. Advances in Neural Information Processing Systems, 28, 802–810.
81. Sperling, J. B., Henriksen, D., Mishra, P., & Seaman, C. (2023). Developing AI literacy: A working framework for education and industry. In M. J. Bishop, E. Boling, J. Elen, & V. Svihla (Eds.), Handbook of research in educational communications and technology (5th ed.). Springer.
82. Stevenson, R. B., & Stirling, C. (2010). Environmental learning and agency in diverse educational and cultural contexts. In R. Stevenson, M. Brody, J. Dillon, & A. Wals (Eds.), International handbook of research on environmental education (pp. 236–244). Routledge.
83. Stoknes, P. E. (2015). What we think about when we try not to think about global warming: Toward a new psychology of climate action. Chelsea Green Publishing.
84. Touretzky, D., Gardner-McCune, C., Martin, F., & Seehorn, D. (2019). Envisioning AI for K-12: What should every child know about AI? In Proceedings of the AAAI Conference on Artificial Intelligence (pp. 9795–9799). AAAI Press.
85. Townsend, A. M. (2013). Smart cities: Big data, civic hackers, and the quest for a new utopia. W. W. Norton & Company.

86. Tuck, E., & McKenzie, M. (2015). Place in research: Theory, methodology, and methods. Routledge.
87. UNESCO. (2021). Recommendation on the ethics of artificial intelligence. United Nations Educational, Scientific and Cultural Organization.
88. United Nations. (2018). The world's cities in 2018. Department of Economic and Social Affairs, Population Division.
89. U.S. Global Change Research Program. (2009). Climate literacy: The essential principles of climate science. USGCRP.
90. Vazquez-Canteli, J. R., & Nagy, Z. (2019). Reinforcement learning for demand response: A review of algorithms and modeling techniques. Applied Energy, 235, 1072–1089. https://doi.org/10.1016/j.apenergy.2018.11.002
91. Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M., & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. Nature Communications, 11, Article 233. https://doi.org/10.1038/s41467-019-14108-y
92. White House. (2023). Executive order on the safe, secure, and trustworthy development and use of artificial intelligence. Office of the Press Secretary.
93. Wiek, A., Withycombe, L., & Redman, C. L. (2011). Key competencies in sustainability: A reference framework for academic program development. Sustainability Science, 6(2), 203–218. https://doi.org/10.1007/s11625-011-0132-6
94. Williamson, B. (2017). Big data in education: The digital future of learning, policy and practice. Sage.
95. Williamson, B., Bayne, S., & Shay, S. (2020). The datafication of teaching in higher education: Critical issues and perspectives. Teaching in Higher Education, 25(4), 351–365. https://doi.org/10.1080/13562517.2020.1748811
96. Winner, L. (1980). Do artifacts have politics? Daedalus, 109(1), 121–136.
97. Wylie, B. (2018). Sidewalk Toronto: A hubristic, insulting, incoherent smart city proposal. Bianca Wylie. https://biancawylie.com
98. Yigitcanlar, T., Han, H., Kamruzzaman, M., Ioppolo, G., & Sabatini-Marques, J. (2019). The making of smart cities: Are Songdo, Masdar, Amsterdam, San Francisco and Brisbane the best we could build? Land Use Policy, 88, Article 104187. https://doi.org/10.1016/j.landusepol.2019.104187
99. Yu, Z., Yao, Y., Yang, G., Wang, X., & Vejre, H. (2020). Strong contribution of rapid urbanization and urban agglomeration development to regional thermal environment dynamics and evolution. Forest Ecology and Management, 446, 214–225.
100. Zhang, J., Zheng, Y., & Qi, D. (2022). Deep spatio-temporal residual networks for citywide crowd flows prediction. Proceedings of the AAAI Conference on Artificial Intelligence, 31(1), 1655–1661.