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Artificial Intelligence in the Educational Infrastructure of Smart Cities: Personalization, Equity, and Governance

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ABSTRACT

Smart cities increasingly integrate educational infrastructure into their technological ecosystems, and artificial intelligence sits at the center of that shift. This paper reviews recent research on AI-enabled educational infrastructure within smart city frameworks, drawing on evidence from adaptive learning platforms, Internet of Things-enabled classrooms, and citywide data governance systems. Three patterns recur across the literature. First, AI-driven personalization produces measurable gains in engagement and performance, with reported improvements ranging from moderate to substantial depending on the depth of implementation. Second, these same technologies risk widening the digital divide when infrastructure, teacher training, and policy support fail to keep pace with adoption, particularly in rural and under-resourced regions. Third, data privacy and algorithmic accountability remain unresolved concerns that shape how much trust educators and communities place in these systems. The paper argues that educational infrastructure in smart cities cannot be judged on technical performance alone; equity and governance determine whether AI narrows or widens the gaps that already exist. Implications for policymakers, school leaders, and urban planners are discussed.

1. Introduction

Cities have started teaching. Not literally, but the sensors, platforms, and algorithms that make a city “smart” now reach directly into classrooms, learning management systems, and student records. A decade ago, smart city research concentrated on traffic, energy, and public safety. Education entered the conversation almost as an afterthought. That has changed. Yigitcanlar *et al.* found that education was among the most frequently discussed application areas in their systematic review of AI and smart cities, sitting alongside transport and governance rather than trailing behind them [1].

The reason is not mysterious. Urban education systems generate enormous quantities of data, and artificial intelligence is good at finding patterns in exactly that kind of data. Attendance records, assessment scores, behavioral logs, and even classroom sensor readings become inputs for systems that promise to personalize instruction, flag struggling students early, and allocate scarce teaching resources more efficiently. Shvets *et al.,* [2] reported a 20% improvement in academic performance

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and 90% user satisfaction after deploying an AI-driven educational ecosystem across multiple institutions within a smart city framework. Numbers like that explain the enthusiasm.

They do not explain everything, though. The same body of research that documents gains in personalization also documents a widening gap between institutions that can afford the infrastructure and those that cannot [3, 4]. It documents unresolved questions about student data privacy [5, 6], and it documents teachers who are still not sure how to use the tools they have been handed [7, 8]. This paper works through those three threads together: what AI actually does inside smart city educational infrastructure, who benefits and who gets left out, and what governance questions remain open. The goal is not to settle the debate. It is to lay out where the evidence currently stands.

2. Literature Review

2.1 Defining Smart City Educational Infrastructure

A smart city, in the definition Yigitcanlar *et al.,* [1] used for their review, is an urban environment where community, technology, and policy work together to deliver productivity, livability, sustainability, and good governance. Educational infrastructure fits inside that definition unevenly. Bašić *et al.,* [9] described it as the layer of information systems, cloud platforms, and AI tools that connect schools to the broader smart city network, supporting what they called Education 4.0: personalized learning, automated assessment, and resource management operating at city scale rather than at the level of a single school.

That framing matters because it shifts the unit of analysis. A single AI tutoring system inside one classroom is not, by itself, smart city infrastructure. It becomes infrastructure when it links into shared data systems, when its outputs feed into district-level planning, and when its physical components, from sensors to connectivity to computing power, depend on the same networks that run the rest of the city. Adel [10] traced this convergence through the transition from Industry 4.0 to Industry 5.0, arguing that intelligent tutoring, robotics, and IoT no longer function as separate initiatives but as interlocking components of a single smart education architecture.

2.2 Personalization and Adaptive Learning

The clearest and most consistently reported benefit of AI in this space is personalization. Multiple studies describe systems that track student performance in real time and adjust content accordingly. Shaikhislamov *et al.,* [11] built an adaptive platform that analyzes achievement, preferences, and learning style to generate individualized trajectories, and argued this reduces teacher workload while improving inclusion. Wang and Song [12] took a similar approach using reinforcement learning and IoT sensors, and found the system cut learning time while improving quiz accuracy, with performance holding steady even as data volume grew.

Intelligent tutoring systems represent the older, more established branch of this work. López-Goyez*et al.* [13] reviewed the literature on intelligent tutoring within smart learning environments and found the field converging on student-centered models that combine learning analytics with adaptive content delivery, most often built on top of existing platforms rather than from scratch. Mohamed and Lamia [14] tested one such system in a flipped classroom setting and found that perceived usefulness and self-efficacy predicted whether students kept using it, a reminder that the technology's success depends as much on how it fits into existing habits as on its underlying algorithm.

Gomede *et al.,* [15] took a different angle, applying random forest classification to a Brazilian elementary school dataset to build knowledge profiles for individual students. Their model did not just predict performance. It generated recommendations educators could act on, which is closer to what a functioning smart city system needs than a prediction score alone. Embarak [16] pushed further into explainability, combining explainable AI with the Internet of Behaviour to track how well existing systems actually responded to documented student needs. The finding was mixed: sophisticated systems existed, but most had not reached the point where they could adapt to individual cognitive needs without face-to-face support filling the gaps.

2.3 Physical Infrastructure: IoT and Smart Classrooms

Personalization software depends on physical infrastructure that most discussions of AI in education skip past. Smart boards, sensors, and connected devices are not incidental. Ibragimova *et al.,* [17] described how IoT-enabled classrooms combine environmental controls, automated attendance through facial recognition or RFID, and AI-driven analytics into a single operating environment, one where a chatbot answers routine questions so instructors can focus on the parts of teaching that actually require a person. Neelakantan *et al.,* [18] built a comparable system with dual-factor authentication and an EcoSmart Campus module that autonomously manages lighting, air quality, and temperature, treating the classroom itself as a piece of city infrastructure rather than a self-contained room.

Kamruzzaman *et al.,* [19] connected this physical layer directly to sustainability goals, arguing that AI and IoT together let cities deliver personalized, real-time educational support even during disruptions like the COVID-19 pandemic. Their point, that resilience and personalization are related outcomes of the same infrastructure, comes up again in Asraf and Hussain [20], whose EduMap system converts unstructured learning materials into interactive mind maps using transformer-based natural language processing. They frame this explicitly as infrastructure for connected learning inside connected cities, a tidy way of stating what much of this literature is really arguing: the classroom and the city are no longer separate systems.

2.4 The Equity Problem

Here the evidence turns less encouraging. Every gain in personalization documented above assumes reliable connectivity, functioning devices, and institutional capacity to maintain them. Those assumptions do not hold everywhere, and the research on this point is unusually consistent across very different national contexts.

Vesna [3] reviewed the barriers directly: infrastructure gaps, socioeconomic constraints, digital literacy deficits, and weak policy support, all of which fall hardest on marginalized communities and underfunded institutions. Imran *et al.,* [21] found the same pattern in interviews with teachers and school heads in Mardan, Pakistan, where inadequate infrastructure and the absence of clear AI policy limited adoption regardless of teachers' willingness to use the tools. Srivastava and Jain [22] quantified the gap in India: 80% of urban higher education institutions had adopted AI tools compared with 45% of rural institutions, a difference their chi-square test confirmed was statistically significant and not just noise in the data.

The pattern repeats itself outside South Asia. Liu and Zhang [23] spent six months in Chinese primary schools across urban, suburban, and rural settings and found four layers of inequality stacking on top of each other: policy decisions that favored elite urban schools, regional stratification under a supposedly uniform national policy, the intergenerational transfer of cultural and economic advantage, and individual gaps in AI literacy that they called a “new digital divide” distinct from older access-based divides. Their conclusion challenges a comfortable assumption running through much of the personalization literature, that AI naturally democratizes access to good instruction. It does not do that automatically. It reproduces whatever inequality already exists in the system it is deployed into, and sometimes it sharpens it [24, 25].

Generative AI has not solved this. If anything, it has made the mapping more complicated. Jamal Eddine *et al.,* [26] mapped the emerging research on GenAI and digital divide phenomena in higher education and identified four persistent barriers: limited infrastructure and connectivity, insufficient AI literacy, cost, and the absence of equity-focused institutional policy. Regional disparities showed up as particularly severe in Global South case studies, where basic infrastructure constraints, not skill gaps, were the primary obstacle. That distinction matters for policy. A country facing an infrastructure deficit needs investment in connectivity and hardware. A country facing a literacy deficit needs training programs. Treating both as the same problem wastes resources on the wrong intervention [27]

2.5 Ethics, Privacy, and Governance

A second concern runs alongside equity: what happens to the data these systems collect. Huang [5] framed student data privacy as an urgent, unresolved matter, one where the conveniences AI offers come bundled with information security risks that most institutions are not equipped to manage. Nguyen [28] tried to establish whether any global consensus existed on ethical principles for AI in education by analyzing international policy guidelines, and found enough overlap to propose a shared framework, though implementation across institutions remains inconsistent.

Governance frameworks have started to catch up, unevenly. Dhiman *et al.,* [29] examined data privacy, algorithmic bias, accountability, and environmental sustainability together, evaluating how regulatory instruments like the GDPR, the EU AI Act, and OECD AI Principles apply to education specifically. Liang *et al.,* [6] focused on the governance side of the same problem, arguing that education systems need models that balance innovation against privacy rather than treating the two as automatically opposed. Yan *et al.,* [30] proposed one concrete version of that balance: a framework built around a “Trusted Domain” architecture that keeps data collection voluntary, processes it at the network edge rather than centrally, and grounds the whole system in institutional data sovereignty.

Accountability is the harder piece. Zhu *et al.,* [31] categorized ethical risks into three dimensions, technological, educational, and societal, and found that responsibility for algorithmic decisions becomes genuinely ambiguous once systems operate as black boxes. When an AI-driven admissions filter or an automated grading system produces a questionable outcome, it is often unclear who is answerable: the developer, the institution, or the algorithm itself. Nguyen [28] reviewed governance frameworks addressing this gap, including UNESCO's recommendations and the emerging EAGFAL model, and argued that ethics needs to move from an abstract principle into an actual teachable competency, something students and educators practice rather than something written into a policy document nobody reads.

2.6 Teacher Readiness

None of this infrastructure functions without the people running it day to day, and the evidence here is the least settled of the three threads. Ayanwale *et al.,* [32] surveyed teachers on their readiness to teach AI in schools and found willingness outpacing preparation almost everywhere. Yue *et al.,* [33] confirmed the gap at scale, surveying 1,664 K-12 teachers and finding a substantial shortfall in both AI content knowledge and technological knowledge, with attitude toward teaching AI shaped less by demographic factors than by direct prior exposure to the tools.

Trust turns out to matter more than raw competence. Nazaretsky *et al.,* [8] tested this directly with K-12 science teachers using an AI-powered grading tool, and found that simply explaining how the system reached its decisions, compared against how a human expert would, meaningfully increased teachers' willingness to use it. That is a small intervention with a large payoff, and it suggests some of the resistance documented elsewhere in the literature is less about technology aversion than about opacity. Fteiha *et al.,* [34] reached a related conclusion in the UAE, where structural equation modeling showed teacher attitudes predicted classroom AI practices far more strongly than knowledge did, with knowledge affecting practice mainly through its effect on attitude rather than directly.

Institutional context shapes all of this. Elmourad *et al.,* [35] surveyed 602 UAE teachers and found that cultural readiness mattered as much as technical readiness, and that leadership support and infrastructure alignment predicted adoption better than access to tools alone. Ng *et al.,* [36] reached a comparable finding through qualitative work with Canadian educators: teachers were broadly optimistic about generative AI, but named school readiness, their own AI competencies, and student AI literacy as the three biggest obstacles, ones that professional development alone cannot fully resolve without matching investment in infrastructure and policy.

3. Discussion

Three threads run through this literature, and they do not point in the same direction. Personalization research is optimistic almost by design. Studies that build and test a specific AI tool tend to report positive results, partly because the tools that fail to work rarely get written up. Equity research tells a different story, one where the same technologies that personalize instruction for well-resourced students often bypass students in rural or underfunded schools entirely. Governance research sits between the two, documenting frameworks that exist on paper but have not yet closed the gap between principle and practice.

What ties these threads together is infrastructure in the literal sense: bandwidth, hardware, electricity, and institutional capacity. A smart city's educational AI is only as smart as the network underneath it. Srivastava and Jain [22] and Imran *et al.,* [21] both make this point from opposite sides of a continent, and Liu and Zhang [23] makes it again inside a single country where urban and rural schools sit under the same national policy but very different practical conditions. Infrastructure gaps are not a footnote to the AI-in-education story. They are a large part of the story.

Teacher readiness complicates the picture further because it is not purely a technical problem. Nazaretsky *et al.,* [8] found that explaining an algorithm's reasoning improved trust more than describing its accuracy did. That is a finding about human psychology, not about machine learning, and it suggests that smart city planners who focus exclusively on technical deployment while treating teacher buy-in as secondary are solving the wrong half of the problem.

4. Implications and Recommendations

A few implications follow reasonably directly from the evidence reviewed here. Infrastructure investment has to come before or alongside AI deployment, not after it. Rolling out adaptive learning platforms into schools that lack reliable connectivity does not personalize education. It personalizes education for the subset of students whose schools already had the infrastructure, which widens rather than closes existing gaps [3, 4].

Data governance needs to be built into educational AI systems from the start rather than added after a breach or a public complaint. The Trusted Domain approach Yan *et al.,* [30] proposed, keeping data local and processing decentralized, offers one workable model, though it is not the only one, and different jurisdictions will need different regulatory scaffolding depending on existing data protection law.

Teacher training should focus on explainability and trust-building, not just tool operation. Nazaretsky *et al.,* [8] showed this works. Training programs that only cover which buttons to press miss the part of adoption that actually predicts whether teachers keep using the system months later.

Policy frameworks need to distinguish between infrastructure deficits and literacy deficits, because they call for different interventions. Jamal Eddine *et al.,* [26] found regions where the bottleneck was connectivity rather than skill, and building AI literacy programs in a place that lacks basic internet access solves nothing.

5. Conclusion

Smart cities are folding education into their broader technological architecture, and AI sits at the center of that process. The evidence supports real gains: adaptive platforms that improve engagement, IoT-enabled classrooms that free up teacher time, and tutoring systems that catch struggling students earlier than a single teacher managing thirty students could manage alone. None of that is in serious dispute across the studies reviewed here.

What remains unresolved is whether those gains reach the students who need them most. The digital divide research says, consistently and across very different countries, that they often do not. The governance research says the frameworks meant to protect student data and hold algorithms accountable are still catching up to the pace of deployment. And the teacher readiness research says that even where infrastructure and policy are sound, adoption depends on trust that has to be earned deliberately rather than assumed.

Educational infrastructure in a smart city is not just a technical layer bolted onto a school system. It is a policy choice, repeated at every level from national ministries to individual classrooms, about who gets access to the tools and who does not. The technology keeps improving. Whether access keeps pace with it is still an open question, and the answer will depend less on the algorithms themselves than on the decisions made around them.

Conflicts of Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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