

Creative Journal

Volume-04, Issue-1
Year of Publication: August 2026
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Dhaka 1230.
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Ethical Frameworks for AI-Assisted Architectural Decision-Making

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Abstract

As architecture enters the era of algorithmic co-authorship, the profession must navigate a complex ethical terrain shaped by artificial intelligence (AI) meaning computer-based programs that can identify patterns, make decisions and produce language content (Russell & Norvig, 2020). This paper investigates the emerging challenges posed by AI tools in architectural design—ranging from data bias and cultural homogenization to authorship disruption and ecological concerns. Utilizing a qualitative approach integrating an inter-disciplinary literature review, five structured case studies and a synthesis of ethical theory, the paper critiques existing frameworks and proposes a multi-layered model titled S.C.A.L.E. (Situatedness, Co-Creation, Accountability, Localization, Eco systemic Responsibility) to guide ethical AI adoption in architecture. It concludes by offering strategic recommendations for designers, educators, policymakers, and developers to foster an inclusive and just architectural future.

Keywords: Artificial Intelligence in Architecture; Architectural Design Automation; AI Bias in Design; Ethics of AI; Cultural Erasure; Design Authorship; Digital Design Philosophy; Human-Centered Design; Algorithmic Transparency; Architectural Theory and AI.

JEL Classification: D63 – Equity, Justice, Inequality; O33 – Technological Change: Choices and Consequences

1. Introduction

1.1 Background

The development of architecture has always been parallel to the advance of technology. Starting with hand drafting to BIM, and now AI, each technological advancement has reshaped the practice (Oxman, 2017). Artificial intelligence (or AI), as defined for this paper as logic-based computer systems that can carry out tasks that normally would require human intelligence including recognition of patterns, generative content, and probabilistic reasoning (Russell & Norvig, 2020) is an invention of a kind I have never seen before. DALL-E, Space maker, and machine learning Grasshopper plugins are examples of tools which are blending human intention and algorithmic suggestion.

With AI being more involved in the ideation and decision-making processes, a new question emerges for architects: not merely what we can build with machines, but what we should. Given the increasing recognition of the importance of AI ethics, current principles, guidelines, and policies conceived within and by computer science and policy domains were not created to navigate the spatially and culturally-specific realities of architectural practice (Floridi & Cowls, 2019). This becomes our research problem.

1.2 Aim & Objective

This research aims to formulate a rigorously defined fundamental principle guiding the use of AI in architectural decision-making. It pursues three specific objectives: first, provide a definition and categorization of ethical issues generated by AI in architecture; second, assess the ethical implications of existing AI in architectural practice tools; and third, propose a reflective ethical structure adaptable for all architectural production.

1.3 Methodology

This study adopts a qualitative research design, which Creswell & Creswell (2018) identify as appropriate when the research goal is to explore complex social phenomena—such as ethics, meaning, and cultural context—that resist quantification. The methodology proceeds through three integrated phases, illustrated in Figure 1.

The first phase is an Interdisciplinary Literature Review: examining the intersection of AI and architecture, philosophy, and design theory. Sources were drawn from peer-reviewed journals, architectural theory texts, and AI ethics scholarship, prioritizing publications from 2015 onwards.

The second phase is a Case Study Analysis: concentrating on projects where artificial intelligence was engaged Quite a bit with urban or architectural design. The cases were purposively selected following the base case selection setup for explanatory case research from Yin (2018), which helps analytical generalization across multiple empirical examples.

The third phase is an Ethical Synthesis: applying deontological, consequentialist, care, and virtue ethics to spatial decision-making. Applying triangulating these approaches is in fact consistent with current models for applied ethics in modern professional work (Beauchamp & Childress, 2019). This triangulation brings the theoretical basis for these S. C. A. L. E. model.

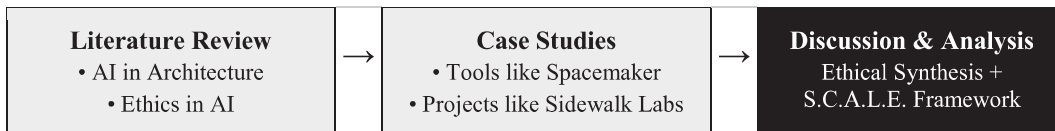


Figure 1: Integrated research methodology. The diagram was constructed by the author to illustrate the three-phase qualitative process: literature review and case studies are conducted in parallel and feed into the discussion and analysis phase, which synthesises findings into the S.C.A.L.E. ethical framework.

1.4 Possible Outcomes

This paper expects multiple contributions. It is intended as an analytical approach of AI assessment in architecture, as well as a design ethics integration tool; as a cause to the ethical blind spot awareness of AIT use in crosscultural and socially perilous environments; and as pedagogical reference through its findings. By addressing architectural theory, philosophy and policy, the paper hopes for an interdisciplinary impact, a structure and starting point for subsequent studies, toward a new realm of ethical, environmental and existential research.

2. Literature Review

2.1 AI in Architecture: Augmentation or Automation?

AI integration into modern architecture can be viewed through three lenses: generative design, performance simulation and data analytics. Each new technology introduction brings with it the promise of increased efficiency and enhanced design opportunities, but further complicates the already present rudimentary friction between the autonomy of creation and computation (Burry, 2011).

In a performative setting, tools like Finch3 or Autodesk's Generative Design engine

facilitate iterative advancement of the configuration enhancing spatial synthesis with multiple outputs. While the breadth of exploration is impressive, critics like Stan Allen argue that such automation risks substituting exploration for judgment. The paradox arises not from an abundance of alternatives, but rather from the absence of dialogue about the prevailing rationale that determines which option is ultimately selected.

Energy optimization, acoustic mapping, daylighting and other forms of performance simulation are routinely deemed objective. Which as Jeremy Till (2009) aptly asserts, "objectivity in architecture is often the mask worn by ideology." The focus placed on quantifiable aspects can overshadow evaluative, cultural, or experiential elements.

Data-driven urbanism, exemplified by AI's predictive models for behavior, traffic, or desirability within a given area, is arguably the epitome of justifying and advancing capitalist and surveillance-based systems (Mattern, 2017). In cases of urban master planning and smart zoning, data-driven profit approaches often compromise community-centric public good.

2.2 Existing Ethical Frameworks and their Gaps in Architecture

Floridi et al.'s (2019) four ethical principles of Accountability, Transparency, Fairness, and Non-maleficence provide a necessary ethical foundation for AI. However, such principles often lack architectural detail. The built environment is as spatial, cultural, and phenomenological as it is technical. Architecture frames how people feel, interact, and belong—dimensions that require a more situated and embodied ethics. Here, Donna Haraway's (1991) theory of a "partial perspective" is especially relevant: systems of ethics must privilege context over abstraction, the multiplicity of lived experience over assuming a normative universal.

And besides, architecture is never merely a question of function or efficiency—it is a question of atmosphere, mood, and meaning. As Peter Zumthor (2010) and Juhani Pallasmaa (2012) argue, buildings are experienced through emotion and the senses. AI, which operates through logic and prediction, lacks this affective literacy. Ethical systems designed for AI must therefore be translated, reinterpreted and ultimately spatialized if they are to contend with the complexity of architectural practice. Otherwise, we risk enforcing generalized systems on spaces that demand nuance, empathy, and cultural sensitivity.

2.3 Research Gap

Despite increased investigation of AI ethics and computational design, the space

between both fields remains underserved. Existing instantiations of AI ethics crafted by computer scientists, policy makers do not cater for the specificities of architecture (spatially, culturally, and phenomenologically). Existing instantiations of architecture theory overly theoretic and lacking way fail to provide a comprehensive set of principles to ethically guide the use of computational AI design tools. This about addresses the problem of this oversight specificity, context, and strategy by introducing the S.C.A.L.E. setup a theoretically written yet operatively centered model that connects generic AI agenesis with the realities of the practices of architecture in culturally heterogeneous contexts (ibid; Smelik, 2008).

3. Key Ethical Challenges

3.1 Bias in Data and Algorithmic Design

The AI models inevitably carry the embedded values, assumptions, and priorities of the data they are trained on. Data is never neutral—it is a product of the social, cultural, economic and political circumstances from which it emerges (Benjamin, 2019). If training data draws on market-driven developments, affluent urban contexts, or Western and Eurocentric building typologies, the AI system literally internalizes those perspectives as normative. The result is therefore a model not only limited in the scope of its knowledge, but one that can actually replicate inequality through its outputs.

For instance, if an AI software used in architectural design is trained on luxury developments—high-end Manhattan apartments with skyline views, minimalist furnishings and innovative technological integrations—it will begin to privilege such spatial and aesthetic properties. They become encoded as "good design" or "high quality" signals, independent of geographic, cultural, or socio-economic context. The AI, in this sense, mirrors real estate capital: accustomed to high-rent potential, market demand, and visual status, but blind to the aspirations and lived experiences of communities outside of that narrow horizon (Costanza-Chock, 2020).

This bias is openly apparent when the same AI is applied to analyze or design in contexts that are fundamentally different from the data on which it has been trained. Think, for example, of Dhaka's Korail slum—a highly dense, informal settlement that has been constructed through necessity, ingenuity and local knowledge. The spatial configurations in Korail may defy the grid-based, property-defined logics of more privileged areas. Paths can be irregular, buildings can develop organically over time, and spaces can have overlapping social and functional uses. To a model trained on formal, commercial architecture, such subtleties are illegible. The model

will flag areas such as these as chaotic, substandard, or in error—not because they are objectively flawed, but because the model lacks the language to see vernacular logics as valid forms of design (Roy, 2005).

This is not merely a technical failure—it is a moral one. The inability of AI to recognize the legitimacy of informal, indigenous, or non-Western spatial practices points to a deeper refusal: a refusal to accept that there are multiple ways of knowing, organizing, and inhabiting space (Haraway, 1991). When AI dismisses or misrepresents such environments, it implicitly devalues the people who create and live in them. It makes cultural and architectural pluralism a problem to be solved, rather than a reality to be understood.

In so doing, AI not only misreads space—it prescribes a hierarchy of design values. It legitimates certain aesthetics and spatial practices and pathologizes others. If we are to use AI in ethical and equitable manners for urban and architectural contexts, we must interrogate the origins and biases of the data we feed into it (Sharma et al., 2023). More importantly, we must diversify the epistemologies that AI is allowed to learn from—privileging not just elite developments, but also vernacular, everyday, and marginalized architectures as valid, in fact essential, sources of design knowledge.

3.2 Loss of Human Judgment and Design Intent

Design is not merely a response to spatial or technical problems—it is, at its core, an expression of ethical judgment (Vallor, 2016). Every design decision reflects a set of values: what to prioritize, whom to include, what histories to acknowledge, and whose lives are being shaped by the built environment. When artificial intelligence enters the design process, particularly through tools that generate massing, layouts, or zoning configurations based solely on performance metrics, the risk is that the ethical dimension of design becomes sidelined.

In this context, the architect or urban planner is no longer the creator, engaging with context, culture, and community. Instead, they may become a curator—selecting from a menu of AI-generated options, each based on abstract criteria that may not align with the nuanced moral landscape of real places. This shift undermines the role of the designer as a moral and civic actor and instead reframes them as a technician fine-tuning outputs generated by opaque systems.

3.2.1 The Problem of "Moral Outsourcing"

Philosophically, this is the issue of moral outsourcing—the delegation of value-laden decisions to a machine that cannot understand ethics, empathy, or human dignity (Matthias, 2004). AI, no matter how advanced, lacks lived

experience. It does not grieve a lost community, celebrate participation in a cultural tradition, or understand the symbolic importance of placing a memorial in a particular site. It optimizes, but it does not care.

Consider, for instance, the location of elder care centers. An AI would recommend locations based on logistics—proximity to hospitals, population density, or transit centers—criteria technically sound. But it might miss the emotional and social realities: how important to situate elders near familiar neighborhoods, within walking distance of family, or within a specific cultural community. These are not inefficiencies; they are moral imperatives that preserve dignity and belonging (Sennett, 2018).

3.2.2 AI and the Loss of Unwritten Values

What is most troubling is that so much of the value embedded in design is unwritten—it is felt, inherited, lived, but not easily codifiable into data (Pallasmaa, 2012). AI cannot perceive cultural symbolism, memory and place, accessibility as justice, or grief and healing. AI systems are not evil or uncaring—but they are ethically neutral. On their own, without active human curation, they will replicate and enlarge the values most legible in their data—often those of market logic, efficiency, and dominant cultural norms.

3.3 Disrupted Authorship and Creative Rights

Authorship in architecture has always been diffuse—between architects, engineers, consultants, and clients. With design being produced by AI, this becomes more complicated. If an AI application creates a layout or building form, who is the author? The architect, the programmer, the developer of the dataset, or the one inputting parameters? Such diffused authorship raises grave legal and ethical questions (Samuelson, 2023).

Intellectual property statutes presume a human author, but AI output violates this. Machine-made designs could be exempt from copyright, and software creators could reserve ownership through terms of license. More pressing than credit is the question of responsibility for harm. If an AI-generated space causes exclusion, gentrification, or safety issues: is the architect responsible for not intervening? Is the developer at fault for training biased algorithms? Or does responsibility vanish in a chain of delegated actions? This is the danger of moral outsourcing: no clear agent to blame, no moral anchor to hold (Matthias, 2004).

3.4 Cultural Homogenization and Aesthetic Loss

AI for architecture is primarily trained on global datasets that are strongly

characterized by Western aesthetics, design norms, and building traditions (Ploennigs & Berger, 2022). The datasets reflect what is widely published, scanned, and indexed—typically modernist, minimalist, high-tech European, North American, and East Asian architecture. Therefore, when AI programs generate forms, facades, or floor plans, they typically reflect a narrow segment of international design awareness.

This bias has concrete consequences. Regional typologies, cultural tropes, and vernacular responses to climate and social existence are erased or suppressed. Consider, for example, the jali screens in Mughal architecture—dashing perforated stone or lattice screens that serve as both decorative art and climatic design, dispersing sunlight and allowing for ventilation and visual seclusion. An AI system optimizing for solar shading might instead suggest a high-performance double-glazed curtain wall, entirely disregarding the profound cultural, symbolic, and spatial significance of the jali (Frampton, 1983). The same applies to courtyard typologies of Bengal, which are profoundly rooted in the socio-spatial lives of families and communities.

Kenneth Frampton's (1983) theory of Critical Regionalism warned against exactly this phenomenon. He argued that the unchecked adoption of global technologies—without anchoring them in local culture, climate, and topography—would lead to the proliferation of placeless architecture. AI, when uncritically applied, can become a digital force for such placelessness.

4. Case Studies

These cases illustrate how AI-powered design software and smart city initiatives can illuminate the promise and pitfalls of algorithmic urbanism. Each of these cases raises core tensions between optimization, ethics, cultural specificity, and public accountability. Cases were selected by purposive sampling (Yin, 2018) to cover different AI application types, geographies, and scales. Table 1 provides a summary before each case is analysed in depth.

Case	AI Application	Geography / Scale	Primary Ethical Issue	Framework Relevance
Space maker AI	Generative site planning	Global / Building–neighborhood	Cultural relevance vs. optimization	Situatedness; Localization
Sidewalk Labs, Toronto	Smart city infrastructure	Canada / Urban	Surveillance; data governance	Accountability; Co-Creation
MIT Moral Machine	Ethical algorithm design	Global / Conceptual	Cultural contingency in encoded values	Localization; Situatedness
Deep Blocks	Real estate AI / protect	Bangladesh (Dhaka) / Urban	Gentrification; displacement	Accountability; Eco systemic Responsibility
AI in Design Studios	Generative tools in education	Global–Bangladesh / Institutional	Authorship erosion; cultural loss	Co-Creation; Localization

Table 1: Summary of case studies selected by purposive sampling (Yin, 2018). All entries are new additions.

4.1 Space maker AI (Autodesk) — Optimization versus Cultural Relevance Ethics

Context: Space maker AI is a generative design software that uses AI to streamline architectural site planning (Autodesk, 2021). It accepts metrics such as daylight access, wind patterns, zoning regulations, and noise to generate building footprints and massing.

Ethical Issue: While Space maker works well in Euro-American contexts where laws are standardized and urban forms are regular, it fails to account for culturally significant design logics in locations with robust vernacular traditions (Frampton, 1983).

Example: In a master plan for Old Dhaka, Space maker produced layouts that were optimal for open space and sunlight exposure but eliminated central courtyards and shaded alleys that are integral to neighborhood life. These provide space for informal economies, social cohesion, and religious practice—functions that optimization metrics are not able to quantify.

Framework Implication: Design ethics must transcend quantifiable parameters to embrace qualitative values—such as historical continuity, symbolism and lived spatial experience. A culturally aware AI would demand human-in-the-loop validation, annotated datasets of regional typologies and context-sensitive decision layers.

4.2 Sidewalk Labs, Toronto — AI Governance and the Ethics of Surveillance

Context: Google's Sidewalk Labs proposed a "smart neighborhood" on Toronto's waterfront. It imagined real-time monitoring of the environment, intelligent infrastructure, AI-optimized building performance and autonomous transport.

Ethical Issue: Despite its innovation, the plan was eventually put on hold due to public outcry regarding data governance, consent, and corporate control of public life (Wylie, 2018; Zuboff, 2019).

Example: The public objected to Sidewalk Labs' suggestion that it monitor residents' activity, energy usage, and behavior, fearing that it was a case of surveillance capitalism. Furthermore, zoning, infrastructure and planning choices were being proposed by a privately held technology firm rather than democratically elected officials.

Framework Implication: Ethically designed architectural AI needs to be built into open, accountable governance systems, involving data ownership, civic participation and public monitoring. AI must be an empowerment technology—not a tool of privatized control of the public sphere.

4.3 MIT Moral Machine — Cultural Contingency in Ethical Algorithms

Context: The Moral Machine project (Awad et al., 2018) explores how AI should make value-laden decisions when outcomes affect human lives. In architecture, AI-assisted tools also make decisions with ethical consequences—though more spatial and long-term.

Ethical Issue: At the core of the Moral Machine is the dilemma of value prioritization: how should machines make decisions that traditionally required human moral judgment? Whose values should be embedded in these algorithms? The study found significant cross-cultural variation in moral preferences (Awad et al., 2018), directly challenging the assumption that ethical decisions can be universally encoded.

Moral Machine Problem	Architectural AI Analogy
Save passengers or pedestrians?	Preserve existing communities or optimize urban form?
Save the young or old?	Prioritize future sustainability or present social needs?
Follow traffic law or act utilitarian?	Respect zoning laws or maximize spatial utility?
Cultural preferences vary	Architectural values vary by region and culture

Table 2: Parallels between Moral Machine dilemmas and architectural AI decisions.

Framework Implication: AI systems used in architectural decision-making must be localized and culturally calibrated. Ethical frameworks must incorporate plural, situated moralities rather than abstract or decontextualized principles.

4.4 Deep Blocks — Bias in Real Estate Algorithms and Urban Gentrification

Context: Deep Blocks is a protect firm that employs AI to automatically analyze real estate. It evaluates zoning regulations, construction costs, and projected return on investment (ROI) to create the most "profitable" development profiles.

Ethical Issue: AI-powered real estate platforms like Deep Blocks are more concerned with profits than with social justice. Because they learn from historical market data, they reflect and even magnify past trends of exclusion, gentrification, and displacement (Benjamin, 2019; Soja, 2010).

Example: In Bangladesh's Badda and Rampura districts—both informal settlement-concentrated areas—AI-driven feasibility tools highlighted hundreds of sites as ideal for high-end residential and commercial development, not accounting for the human cost of redevelopment. Entire blocks, many housing recent climate migrants or low-income service workers, were evicted with no resettlement or compensation programs.

Framework Implication: AI must be evaluated not just on performance, but on social consequence. Ethical frameworks should include tools for impact assessment, inclusionary zoning logic, and displacement risk metrics.

4.5 AI in Academic Design Studios — Automation, Authorship, and Cultural Loss

Context: Software's such as Midjourney, DALL·E, and TestFit are increasingly incorporated into architecture curriculum (Quinn, 2023). They are favored for their efficiency and capability to produce pleasing outputs from text.

Ethical Issue: The increasing application of AI software in studio classes risks undermining architectural authorship and cultural meaning (Henderson et al., 2023). With students increasingly depending on AI results, the rules of place, tradition, material logic, and climatic responsiveness are likely to be compromised.

Example: Shrivastava (2024) observed that students were increasingly using AI tools like Midjourney and DALL·E to generate designs without critical engagement. At the University of Auckland (2025), educators found that while AI facilitated rapid ideation, there were concerns about students becoming over-reliant on AI, potentially compromising the development of foundational design skills and critical thinking.

Framework Implication: Design automation must allow room for human judgment, ethical discernment, and creative nuance. AI systems that are ethical must have affordances for intentionality, interventions by the user and value-based overrides.

5. Proposed Ethical Framework for AI in Architecture

With growing application of artificial intelligence in architectural practice, an enhanced ethical framework is essential to ensure that technological advancement strengthens, rather than weakens, the intrinsic human, cultural, and environmental values of the built environment. A Four-Layered Ethical Framework is presented below to guide the ethical formulation and deployment of AI in architectural contexts.

Layer 1: Human-Centeredness

Objective: Reaffirm the dominance of human values, experience, and sensory perception in AI-aided design processes (Pallasmaa, 2012).

Empathy & Narrative Integration: AI spaces must be anchored in lived human experience. This involves training models to recognize the affective and emotional dimensions of architecture—like comfort, memory, ritual, and identity—based on user narratives, ethnographies, and spatial narratives.

AI as Co-Creator, Not Auteur: The role of AI should be that of a creative assistant—not a substitute for the architect's ethical and aesthetic judgment. Designers must be empowered to override, reinterpret, or reject AI-generated outcomes when they conflict with humanistic intentions.

Layer 2: Transparency and Explainability

Objective: Ensure that AI systems are not "black boxes," but provide transparent justification for their results (Floridi & Cowls, 2019), allowing architects to make sound design decisions.

Interpretable Algorithms: AI applications should come with interfaces that allow users to visualize how each variable influenced the final output. This encourages critical thinking and not blind faith.

Justification Rather Than Output: AI software should not only deliver solutions; they should also highlight why a solution is best, including compromises in ventilation, daylight, or public space.

Layer 3: Contextual Justice

Objective: Prevent homogenization of architecture through implanting local, cultural, and socio-spatial sensibility in AI systems (Frampton, 1983; Costanza-Chock, 2020).

Varied Training Data: Architectural examples representing different geographies, socio-economic contexts, and vernacular tradition must be trained in AI models to avoid reinforcing Eurocentric or modernist design tropes.

Ethical Geofencing: AI software should adapt their design ethos according to regional culture, climate, legislation, and cultural requirement.

Spatial Equity Integration: AI needs to be developed to consider distributive justice—offering equitable access to light, air, greenery, mobility, and public space.

Layer 4: Participatory Governance

Objective: Democratize AI use in architecture through collective regulation, inclusive dialogue, and ethical accountability (Sennett, 2018).

Community Engagement in AI Decisions: In collective projects, AI-calculated alternatives need to be co-assessed with affected communities through charrettes, workshops, or online comment tools.

Ethics Oversight Commissions within the Discipline: Architecture firms using AI technology need to have in-house ethics oversight commissions—composed of designers, ethicists, social scientists, and data analysts.

6. Discussion

Artificial intelligence in architecture should not be understood as a value-neutral instrument but as an active participant in design that carries with it inherent assumptions and biases (Winner, 1980; Benjamin, 2019). It does not merely automate, but rather makes choices that influence spatial forms, social encounters, and cultural representation. Every AI-produced outcome reflects the values of data on which it is trained and optimized to achieve, whether to maximize daylight, minimize cost, or maximize density. These are not value-neutral choices; they decide how individuals live, engage, and experience space.

This world requires a transformation of architectural education. It is not sufficient that students can operate AI software; they must develop critical software literacy—the ability to challenge datasets, decipher algorithmic purpose, and evaluate the spatial and cultural impact of machine decision-making (Vallor, 2016). Architectural pedagogy must adapt to include ethical and critical examination of technology, considering software not just as a means to an end but as an agent of culture requiring interpretation and critique.

Furthermore, AI ethics in architecture must be imagined beyond lawfulness or technicality. Ethics must be embraced as a spatial and lived matter (Pallasmaa, 2012; Till, 2009). The most important question is not so much whether AI is ethical or transparent, but what living in an AI-designed environment is like. Does it support belonging, dignity, and cultural expression—or does it lead to sanitized, optimized environments devoid of human needs?

Unless interrogated, AI risks reproducing prevailing architectural canons and discrediting local practice (Frampton, 1983; Roy, 2005). But when used responsibly, it can allow for inclusive, context-specific, culturally grounded design. Ethical practice with AI must therefore be based on both critical understanding and spatial empathy—not only what we can accomplish with AI, but how and for whom.

The five case studies presented in this paper together demonstrate that these risks are 'not an abstraction'; both the Frampton (1983) critique of placeless universalism in the Space maker case and the validation of Zuboff (2019) system of surveillance capitalism in the G.S.B. case; the echoing of Haraway (1991) insight that no perspective is more neutral and universal than any other through the Moral Machine study; the confirmation of Benjamin's (2019) demonstration that outcome-based automated decision-making continues to reproduce structural inequality through the Deep Blocks case; and the reaffirmation of the Vallor (2016) observation that the conveniently automated lifestyle erodes professional virtue through the design studio cases all are evidentiary manifestations of the S.C.A.L.E. system I offer in this paper.

7. Strategic Recommendations for Implementing the S.C.A.L.E. Framework

In line with the S.C.A.L.E. Ethical Framework for AI in Architecture, the following are overarching strategies and suggestions for implementation—addressing architects, design practice, academia, AI developers, and policymakers:

7.1 Situatedness

Objective: Render AI systems context-aware and embedded in local realities.

Strategies: Create region-specific training datasets that include vernacular architecture, climatic information, and user behavior patterns from the Global South. Develop "context cards" that must be filled out before AI use is allowed—full of site climate, topography, socio-cultural data, and user demographics. Include participatory mapping tools (e.g., Maptionnaire, Ushahidi) (Bittner et al., 2021) to record local spatial desires and practices.

Recommendations: To academia: Encourage design studios that integrate AI tools and ethnographic fieldwork. To software developers: Include location-aware defaults and filters by climate zone or cultural typology. For practitioners: Require all AI-generated proposals to include a "context rationale" with site-specific justifications.

7.2 Co-Creation

Objective: Turn AI into a creative collaborator, not a dictator.

Strategies: Develop modular AI tools that allow architects to modify, override, and layer their own interpretations on top of AI-generated designs. Teach students and professionals "prompt literacy." Develop co-design workshops with architects, clients, and communities alongside AI interfaces.

Recommendations: For design practice: Use tools like Midjourney, Test Fit or Space maker in iterative feedback loops, not for final outcomes. For AI developers: Create features to allow side-by-side comparison of AI vs human-generated options. For architecture journals: Publish AI-human hybrid design case studies to set precedents for collaborative authorship.

7.3 Accountability

Objective: Make the ethical chain of decision-making traceable and transparent.

Strategies: Implement AI audit trails in BIM or design software that log what suggestions came from AI and how they were changed. Set up AI Ethics Review Boards in architectural practices and public authorities for vulnerable projects.

Recommendations: To policymakers: Mandate AI transparency reporting in planning submissions for public projects. For academia: Develop AI Ethics Toolkits for Architects with questions like: "Who trained this model?", "Whose values does it encode?"

7.4 Localization

Goal: Make AI attuned to legal, cultural, and ecological difference.

Strategies: Collaborate with national standards organizations to integrate local building codes and planning law into AI datasets. Launch "Local AI" initiatives that develop open-source models trained on non-Western architecture. Develop cultural sensitivity audits that alert when AI designs transgress local values.

Recommendations: To governments: Open spatial datasets and planning documents for training location-specific AI. To AI developers: Allow users to

customize models with cultural and regulatory presets. For NGOs: Enable local communities to digitalize indigenous knowledge and claim data rights.

7.5 Eco systemic Responsibility

Goal: Align AI-assisted design with environmental justice and long-term sustainability (UNEP, 2021).

Strategies: Integrate carbon footprint analysis, material lifecycle analysis, and biodiversity metrics directly into design software. Create "climate adaptive" AI modes that generate design variations based on IPCC climate projections for the region. Promote zero-waste and regenerative design principles in algorithmic output.

Recommendations: For schools: Integrate environmental ethics modules into computational design education. For property developers: Promote AI use that reconciles profit and green equity metrics. For international organizations: Fund AI for Climate-Resilient Architecture initiatives in climate-vulnerable nations like Bangladesh.

Integrated Implementation Matrix

S.C.A.L.E. Layer	Key Actors	Tools/Methods	Policy Suggestions	Framework Layer
Situatedness	Educators, Urban Planners	Context Cards, Participatory Mapping	Require local adaptation analysis in AI reports	Layer 1, 3
Co-Creation	Architects, Students	Prompt Literacy, Human-AI Hybrid Workflow	Guidelines for AI-human attribution in competitions	Layer 1, 2
Accountability	Firms, Governments	Audit Logs, Ethics Boards	Mandatory AI-use disclosure for public projects	Layer 2, 4
Localization	Developers, NGOs	Cultural Presets, Legal Integration	Public data platforms for localized AI training	Layer 3, 4
Eco systemic Responsibility	Researchers, Climate Bodies	Embedded Carbon Metrics, Climate-Adaptive Modes	Reward regenerative AI design in urban policy	Layer 1, 3

Table 3: S.C.A.L.E. Integrated Implementation Matrix

8. Conclusion

As architecture approaches a future of algorithmic co-authorship, it is critical that the profession not relinquish its moral agency to convenience by technology. Artificial Intelligence holds enormous power to exploit the speed, efficiency, and creativity of design processes. That power becomes morally risky if it is exercised without reflectiveness, cultural sensitivity, and social equity concerns.

AI is not a value-free assistant; it is shaped by the training data that it is exposed to, the functions that it is designed to fulfill, and the presuppositions built into its algorithms (Winner, 1980). Employed naively, it can replicate homogenized aesthetics, reinforce institutional biases, and push to the margins local building knowledge—especially in the Global South. Thus, architects must become the ethical guardians, ensuring that AI systems are designed in line with not only design aims but also the core ethics of justice, sustainability, and human dignity.

The S.C.A.L.E. Framework outlined in this paper is a many-sided process towards this moral alignment. Placing situatedness, co-creation, accountability, localization, and ecosystemic responsibility at the center, it offers an integrated framework to tackle the ethical challenges of AI in building design. It reasserts that architecture's future should be equally focused on where and for whom we build, as on how we calculate and construct form.

Besides, architectural education will have to adapt to acculturate future practitioners not only as competent users of computational software but as thinkers and ethical actors (Vallor, 2016). Architects in the future must be as literate in philosophical discourse as in parametric programming—able to critique algorithms, resist datasets, and challenge the illusion of technological neutrality. Ultimately, we are not aiming to build alone more quickly or more efficiently, but wiser, more inclusive, and more fairly.

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