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Artificial Intelligence Adoption in Architectural Practice: Challenges and Opportunities in Developing Countries

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Abstract

Artificial intelligence (AI) is projected in transforming architectural practice worldwide, yet its adoption in developing countries remains uneven and under studied. This study examines the challenges and opportunities associated with AI adoption among practising architects in developing country contexts, with particular attention to Sub-Saharan Africa, South Asia, and Southeast Asia. A mixed-methods design combining a structured online survey (n = 142) of practising architects and semi structured interviews (n = 15) with senior practitioners and academics was employed. Findings indicate that infrastructural limitations, licensing costs, inadequate training pathways, and data scarcity are the most significant barriers to adoption, while generative design for affordable housing, climate responsive simulation, and the digitisation of vernacular building knowledge represent the most promising areas of opportunity. The study concludes that targeted investment in local training infrastructure, tiered software pricing, and regulatory modernisation could substantially accelerate responsible AI adoption in these contexts. The paper offers a framework for policymakers, educators, and technology developers seeking to support equitable AI integration in the built environment sector.

Keywords: Artificial Intelligence, Architecture, Developing Countries, Generative Design, Sustainable Building, Technology Adoption

INTRODUCTION

The global architecture, engineering, and construction (AEC) sector is undergoing a period of rapid technological transformation, driven in large part by advances in artificial intelligence. Generative design platforms, machine learning based energy simulation tools, and AI assisted building information modelling (BIM) workflows have moved from experimental use to mainstream practice in many high-income countries (Autodesk, 2023; RIBA, 2022). In developing countries, however, adoption of these tools has lagged considerably behind, despite these regions often facing the most urgent architectural challenges: rapid urbanisation, acute housing shortages, and climate vulnerability.

This uneven adoption raises an important research question, what specific factors constrain and enable AI adoption among architects working in developing-country contexts, and how might these factors be addressed? While a growing body of literature examines AI in architecture broadly (Chaillou, 2022; As, Pal & Basu, 2021), relatively few studies focus specifically on the structural, economic, and institutional conditions that shape adoption in low- and middle-income countries. This study addresses that gap through an empirical investigation of practising architects across three developing regions.

The objectives of this study are to:

i. identify the principal barriers to AI adoption in architectural practice in developing countries;
ii. determine the opportunities that AI presents for addressing region specific design and development challenges; and
iii. propose recommendations for practitioners, educators, and policymakers.

AI Applications in Architectural Practice

AI applications in architecture span generative design, performance simulation, construction robotics, and predictive project management. Generative design tools use algorithms to produce and evaluate large numbers of design alternatives against defined constraints such as cost, structural performance, and daylighting (Chaillou, 2022; Castro Pena et al., 2021). Recent systematic reviews indicate that adoption of generative AI in architectural practice has accelerated sharply since 2021, with growing use of diffusion models and transformer-based tools alongside earlier generative adversarial network approaches (Jang, Roh, & Lee, 2025; Li, Zhang, Du, Zhang, & Xie, 2024; Zhang & Zhang, 2024). Machine learning models are increasingly applied to energy and thermal comfort simulation, allowing architects to test passive design strategies without costly physical prototyping (Wortmann & Nannicini, 2021; Abdeyazdan, Safaeianpour, & Amini, 2025; Yuan et al., 2025), including explainable AI approaches that link building form and envelope parameters directly to cooling and heating loads in hot and arid climates (Eshraghi, Talami, Nikkhah Dehnavi, Mirdamadi, & Zomorodian, 2024; Płoszaj-Mazurek, Ryńska, & Grochulska-Salak, 2020).

Technology Adoption

Technology adoption theory suggests that infrastructure, cost, perceived usefulness, and institutional support jointly determine the diffusion of new tools within a profession (Rogers, 2003; Venkatesh et al., 2003). Studies of digital technology adoption in developing-country construction sectors consistently identify connectivity, cost, and skills gaps as primary constraints (Oke, Aigbavboa & Semenya, 2018). This pattern is especially well documented for Building Information Modelling, where systematic reviews and country-level studies across the Middle East, North Africa, and Sub-Saharan Africa point to high licensing and hardware costs, limited local training, weak regulatory mandates, and organisational resistance to change as dominant barriers (El Hajj, Martínez Montes, & Jawad, 2023; Kineber et al., 2023; Takyi-Annan & Zhang, 2023; Saliu, Monko, Zulu, & Maro, 2024; Rinchen, Banihashemi, & Alkilani, 2024; Ndwandwe, Kuotcha, & Mkandawire, 2024), consistent with earlier accounts of skills mismatches and slow technology uptake in the South African construction sector (Windapo & Cattell, 2013; Froise & Shakantu, 2014). However, these same contexts have also demonstrated a capacity for 'leapfrogging' bypassing legacy technology generations entirely, as seen in mobile financial services across parts of Africa (World Bank, 2022; James, 2009, 2012), even as scholars caution that inclusion in a digital system does not automatically translate into equitable benefit for all who are incorporated into it (Heeks, 2022).

Gaps in the Literature

Existing studies on AI in architecture are disproportionately drawn from high-income contexts, with limited empirical data on practitioner experiences in developing countries. Where studies do exist, they tend to focus narrowly on technical feasibility rather than the socio-economic and institutional conditions that determine real world adoption. This study contributes empirical, practitioner-level data to address that gap.

Research Design

This study adopted a convergent mixed methods design, integrating quantitative survey data with qualitative interview data to develop a comprehensive understanding of AI adoption patterns. This approach was selected to capture both the prevalence of specific barriers and opportunities (quantitative) and the contextual reasoning behind them (qualitative).

Sampling and Participants

A purposive and snowball sampling strategy was used to recruit practising architects from Sub-Saharan Africa, South Asia, and Southeast Asia. The survey link was distributed electronically through professional architecture associations, university alumni networks, and social media professional groups between June 2026 and August 2026. Because distribution partly relied on open association and social-media channels without a fixed sampling frame, a precise response rate could not be calculated; this is noted as a limitation below. A total of 142 valid survey responses were obtained from architects across 14 countries. Fifteen semi-structured interviews were subsequently conducted with senior architects, firm principals, and academics, purposely selected to ensure representation across all three regions, a spread of firm sizes, and a mix of practice-based and academic perspectives.

Table 1: Regional distribution of survey and interview participants

Region	Survey respondents, n (%)	Interview participants, n
Sub-Saharan Africa	87 (61.3%)]	7
South Asia	42 (29.5%)]	5
Southeast Asia	13 (9.2%)]	3
Total	142 (100%)	15

Source: Author's Fieldwork (2026)

Data Collection Instruments

The survey instrument comprised 28 items across four sections:

i. demographic and firm profile,
ii. current AI tool usage,
iii. perceived barriers to adoption, and
iv. perceived opportunities.

Items used five point Likert scales alongside multiple choice and open response questions. The interview protocol consisted of 12 open ended questions exploring participants' direct experiences with AI tools, institutional support, and views on future adoption.

The survey instrument was piloted with 5 practising architects prior to full deployment to check item clarity, question flow, and completion time; minor wording revisions were made following the pilot and pilot responses were excluded from the final analysis. Internal consistency of the multi-item Likert scales in the Barriers and Opportunities sections was assessed using Cronbach's alpha with values above 0.70 indicating an acceptable reliability.

Ethical Considerations

Ethical approval for the study was obtained prior to data collection. Participation in both the survey and interviews was voluntary, and informed consent was obtained from all participants. Survey responses were collected anonymously; interview participants were assigned anonymised codes (P1–P15) and identifying firm details were removed from transcripts prior to analysis. Interview recordings and transcripts were stored on a password-protected, encrypted institutional drive accessible only to the research team.

Data Analysis

Quantitative survey data were analysed using descriptive statistics (frequencies and percentages), computed in Python (pandas, version 2.2). Given the ordinal nature of the Likert-scale items, differences in barrier and opportunity ratings across regions and firm sizes were additionally examined using Kruskal Wallis tests; because per-region and per-firm-size subgroup sizes are modest, these comparisons are reported as exploratory rather than confirmatory. Qualitative interview data were audio-recorded, transcribed verbatim, and analysed thematically following Braun and Clarke's (2006) six-phase inductive approach. Resulting themes were then compared against the quantitative survey findings to assess convergence and divergence across the two data sources.

Limitations

As with most purposive-sample studies, findings are not statistically representative of the full population of architects in developing countries and should be interpreted as indicative rather than generalizable. Self-selection bias is also possible, as architects with an existing interest in technology may have been more likely to participate, which may inflate reported awareness of and interest in AI tools relative to the wider profession. Because a precise sampling frame could not be established for association- and social media distributed responses, an exact response rate could not be calculated. Data collection and both instruments were conducted in English only, which may have limited participation from architects more comfortable working in other languages and could under-represent certain sub populations within the three regions studied. Finally, pooling three large and internally diverse regions into a single primary analysis, while necessary given region-level sample sizes, may obscure meaningful within-region variation; regional breakdowns are reported where sample size allows (Table 1) and should be read as indicative.

RESULTS

Participant Profile

Of the 142 survey respondents, 61% worked in firms of fewer than 10 employees, 27% in mid-sized firms (10-50 employees), and 12% in large firms or public institutions. Respondents were drawn from 14 countries across the three target regions, most frequently Nigeria, Kenya, Ghana, India, Bangladesh, Indonesia, and the Philippines, with average professional experience of 8.4 years. The regional distribution of respondents is reported in Table 1 above region specific results below are noted as exploratory given the resulting subgroup sizes.

Current Levels of AI Tool Use

Only 23% of respondents reported regular use of any AI enhanced design or analysis tool, while 39% had experimented with such tools on a limited or trial basis, and 38% reported no use at all. Among current users, energy/thermal simulation tools and AI assisted rendering were the most commonly used applications; generative design and predictive project-management tools were used by fewer than 10% of respondents.

Barriers to Adoption

Table 2 summarises the barriers most frequently rated as 'significant' or 'very significant' by survey respondents (n = 142).

Barrier	% Rating as Significant/Very Significant
Cost of software licensing/subscriptions	83%
Unreliable internet connectivity/power supply	71%
Lack of local training opportunities	68%
Absence of region-specific data (climate, materials)	59%
Regulatory bodies unequipped to review AI-assisted designs	47%
Client or senior staff resistance/distrust	41%

Table 2: Barrier Significant rating

Source: Author's Fieldwork (2026)

Interview data reinforced these findings: 12 of 15 interviewees described licensing costs as prohibitive relative to local fee structures, and 9 of 15 cited the absence of structured, affordable local training as a persistent obstacle to building in house capability.

Perceived Opportunities

Respondents were also asked to rate the potential value of AI applications specific to their working context. Table 3 presents the applications rated as offering 'high' or 'very high' potential value.

Opportunity Area	% Rating as High/Very High Value
Rapid generation of low-cost housing layouts	82%
Climate-responsive design simulation (passive cooling, ventilation)	77%
Reduced need for physical prototyping/testing	64%
Integration of vernacular/traditional design knowledge	58%
Access to international project/funding opportunities	52%

Table 3: Opportunity Area applications rating

Source: Author's Fieldwork (2026)

Qualitative Themes

Thematic analysis of interview data, cross checked by a second coder as described in the Methodology, produced four dominant themes.

i. infrastructure before innovation - participants consistently framed connectivity and cost as prerequisite conditions rather than secondary concerns
ii. training as the real bottleneck - even where tools were financially accessible, participants reported limited confidence in using them effectively
iii. design relevance - several participants expressed concern that AI tools trained on foreign datasets produced recommendations poorly suited to local climates and materials
iv. cautious optimism - despite these concerns, a majority of interviewees expressed strong interest in AI's potential to address housing shortages and climate responsive design challenges specific to their regions

DISCUSSION

The findings are consistent with AI adoption among the architects surveyed being shaped less by a lack of interest and more by structural constraints - cost, connectivity, and training - that mirror broader patterns of digital technology adoption identified in prior literature (Oke et al., 2018; World Bank, 2022). Because the design is cross-sectional and the sample non-probability, these associations should be read as descriptive rather than causal. Notably, the strong interest expressed in generative design for affordable housing and climate-responsive simulation suggests that demand for AI tools among these respondents is closely tied to problems they consider most pressing in their own contexts, rather than to global trends in AI design aesthetics; testing this pattern in a larger, more representative sample is an important direction for future research.

The concern raised by several interview participants around foreign-trained datasets producing contextually inappropriate recommendations is a noteworthy finding, though it rests on a small number of qualitative accounts and warrants confirmation through larger, dataset-focused research before firm conclusions are drawn. If borne out, it would suggest that AI adoption in these contexts cannot simply mean importing tools developed for other markets; meaningful adoption may require investment in regionally relevant datasets and, potentially, locally developed models.

These findings are broadly consistent with, though do not directly test, the 'leapfrogging' hypothesis discussed in the literature review (James, 2009, 2012), which mirrors the pattern of rapid mobile-technology diffusion seen elsewhere on the continent (World Bank, 2022); the evidence offered here is qualitative and illustrative rather than confirmatory. Most of the interview participants noted that their firms had never invested heavily in legacy CAD-only workflows and were, as a result, more open to adopting cloud-based, AI-native tools directly - provided cost and connectivity barriers could be addressed.

CONCLUSION AND RECOMMENDATIONS

This study provides empirical evidence that AI adoption in architectural practice within developing countries is constrained primarily by structural and economic barriers rather than by professional disinterest. At the same time, architects in these contexts see substantial, context specific value in AI applications particularly for affordable housing design and climate-responsive architecture. Based on these findings, the study offers the following recommendations:

i. Software developers should consider tiered, purchasing-power-adjusted pricing models for markets in developing countries.
ii. Architecture schools and professional bodies should integrate computational design and AI literacy into curricula and continuing professional development programmes, an imperative increasingly recognised in the wider AEC literature on upskilling for generative AI (Onatayo et al., 2024).

iii. Governments and international development agencies should invest in the digitisation of local climate, material, and geotechnical datasets to improve the contextual relevance of AI tools.
iv. Regulatory and building-approval bodies should develop clear frameworks for reviewing AI-assisted architectural submissions.
v. Future research should examine longitudinal adoption patterns as tools and training infrastructure evolve, and should expand sampling to include Latin American and Central Asian contexts not covered in this study.

References

Abdeyazdan, H., Safaeianpour, A., & Amini, M. A. (2025). Explainable machine learning for passive design: Early-stage building energy reduction in hot-arid climates. Sustainable Energy Technologies and Assessments.

As, I., Pal, S., & Basu, P. (2021). Artificial intelligence in architecture: Generating conceptual design via deep learning. *International Journal of Architectural Computing*, *19*(1), 5–22.

Autodesk. (2023). The state of design and make: AI in the AEC industry. Autodesk Research Report.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101.

Castro Pena, M. L., Carballal, A., Rodríguez-Fernández, N., Santos, I., & Romero, J. (2021). Artificial intelligence applied to conceptual design: A review of its use in architecture. *Automation in Construction*, *124*, 103550.

Chaillou, S. (2022). ArchiGAN: Artificial intelligence for architectural generative design. In Architectural Intelligence (pp. 117–127). Springer.

El Hajj, C., Martínez Montes, G., & Jawad, D. (2023). An overview of BIM adoption barriers in the Middle East and North Africa developing countries. Engineering, Construction and Architectural Management, 30(2), 889–913.

Eshraghi, P., Talami, R., Nikkhah Dehnavi, A., Mirdamadi, M., & Zomorodian, Z.-S. (2024). Adopting explainable AI to investigate the impact of urban morphology design on energy and environmental performance in dry-arid climates. arXiv preprint arXiv:2412.12183.

Froise, T., & Shakantu, W. (2014). Diffusion of innovations: An assessment of building information modelling uptake trends in South Africa. *Journal of Construction Project Management and Innovation*, *4*(1), 895–911.

Heeks, R. (2022). Digital inequality beyond the digital divide: Conceptualizing adverse digital incorporation in the global South. *Information Technology for Development*, *28*(4), 688–704.

James, J. (2009). Leapfrogging in mobile telephony: A measure for comparing country performance. *Technological Forecasting and Social Change*, *76*(7), 991–998.

James, J. (2012). The distributional effects of leapfrogging in mobile phones. *Telematics and Informatics*, *29*(3), 294–301.

Jang, S., Roh, H., & Lee, G. (2025). Generative AI in architectural design: Application, data, and evaluation methods. *Automation in Construction*, *174*, 106174.

Kineber, A. F., Othman, I., Famakin, I. O., Oke, A. E., Hamed, M. M., & Olayemi, T. M. (2023).

Challenges to the implementation of Building Information Modeling (BIM) for sustainable construction projects. *Applied Sciences*, *13*(6), 3426.

Li, C., Zhang, T., Du, X., Zhang, Y., & Xie, H. (2024). Generative AI for architectural design: A literature review. arXiv preprint arXiv:2404.01335.

Oke, A. E., Aigbavboa, C. O., & Semenya, K. (2018). Technology adoption in the construction industry of developing economies. Journal of Engineering, Design and Technology, 16(6), 833–848.

Onatayo, D., Onososen, A., Oyediran, A. O., Oyediran, H., Arowoiya, V., & Onatayo, E. (2024). Generative AI applications in architecture, engineering, and construction: Trends, implications for practice, education and imperatives for upskilling—A review. *Architecture*, *4*(4), 877–902.

Płoszaj-Mazurek, M., Ryńska, E., & Grochulska-Salak, M. (2020). Methods to optimize carbon footprint of buildings in regenerative architectural design with the use of machine learning, convolutional neural network, and parametric design. *Energies*, *13*(20), 5289.

RIBA. (2022). Digital transformation in architectural practice: Annual survey report. Royal Institute of British Architects.

Rinchen, S., Banihashemi, S., & Alkilani, S. (2024). Driving digital transformation in construction: Strategic insights into building information modelling adoption in developing countries. *Project Leadership and Society*, *5*, 100138.

Saliu, L. O., Monko, R., Zulu, S., & Maro, G. (2024). Barriers to the integration of Building Information Modeling (BIM) in modular construction in Sub-Saharan Africa. *Buildings*, *14*(8), 2448.

Takyi-Annan, G. E., & Zhang, H. (2023). A bibliometric analysis of building information modelling implementation barriers in the developing world using an interpretive structural modelling approach. *Heliyon*, *9*(7), e18601.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478.

Windapo, A. O., & Cattell, K. (2013). The South African construction industry: Perceptions of key challenges facing its performance, development and growth. *Journal of Construction in Developing Countries*, *18*(2), 65–79.

World Bank. (2022). Digital development in Sub-Saharan Africa: Leapfrogging opportunities. World Bank Group.

Wortmann, T., & Nannicini, T. (2021). Machine learning for building performance simulation. *Building Simulation*, *14*(4), 1–15.

Yuan, L., Yao, J., Zhou, Y., Calautit, J., Huang, C., Fang, Z., Yang, F., Zhao, M., Wang, Y., & Hu, X. (2025). AI-driven passive design optimization for thermal comfort in enclosed courtyard buildings. Case Studies in Thermal Engineering.

Zhang, H., & Zhang, R. (2024). Generative artificial intelligence (AI) in built environment design and planning – A state-of-the-art review. Progress in Engineering Science.