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Artificial Intelligence and Architecture Education in India

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Abstract

In about three years, generative AI has become a normal part of design work. Architecture students in India already use it often, but most schools still have no clear rules for how it should be used. This paper brings together research on three questions: how AI is changing architecture education, why students submit AI-generated work, and which institutional responses actually help. Studies show that AI is most useful at the start of the design process, where it speeds up idea generation and helps produce many polished visuals. It is much less helpful in later stages that need critical judgement, technical accuracy and real originality. Whether AI improves or harms learning depends mainly on how teachers frame and control its use. The evidence on copying is clear but uncomfortable. Current AI-detection tools are unreliable and often label the writing of non-native English speakers as AI-generated. In India, this makes them both unusable and unfair. Experienced teachers also cannot reliably tell AI-generated work from student work just by reading, and giving “real-world” project briefs does not, on its own, stop students from using AI. The research points instead to a set of simple, practical measures: clearly stating how much AI use is allowed for each task, grading the design process and not only the final output, designing assignments that AI cannot complete well, requiring students to declare which tools they used, writing a code of conduct together with students, and reducing workloads and deadline pressure that encourage plagiarism. The paper ends with a year-by-year plan for integrating AI across the five-year B.Arch programme and highlights key topics for future research in India.

Keywords: architecture education; generative AI; academic honesty; assessment; design studio; AI literacy; India; Council of Architecture

1. Introduction

Architecture education has consistently been shaped by the tools available to students. The drawing board, physical models, CAD and BIM each transformed not only modes of representation but also the ways in which students conceptualised their designs. Generative AI is the most recent addition to this lineage and differs in two significant respects. First, it intervenes at the outset of the design process rather than at its conclusion, precisely where architecture schools concentrate most of their teaching. Second, its adoption has been abrupt: systems such as Midjourney, Stable Diffusion, DALL-E and ChatGPT diffused among students within months, well before curriculum authorities could respond.

These developments have created a clear misalignment between students' actual practices and institutional planning. A survey of 97 teachers and 324 students across 32 countries found that AI tools are already in wide use. While most teachers acknowledged this reality, students were largely engaging with AI independently, without structured guidance

from their institutions. The resulting work was often of limited quality, and very few students had received formal training (Ghonim, Eweda, and Elshater 2026). Research in Saudi Arabia identified an even sharper divide: students reported confidence and enthusiasm, whereas teachers expressed concern that AI would undermine independent thinking, although both groups agreed that AI should be incorporated into the curriculum (Alshahrani, Dahlan, and Al-Zahrani 2025). Another study focusing on student perspectives highlighted a critical distinction: a positive attitude towards AI does not equate to effective use. In the absence of explicit instruction, favourable views alone do not lead to competent practice (H. and ürk 2026).

India has particular reasons to attend to these trends. It operates one of the world's largest systems for architectural education, with approximately 365 institutions participating in the 2025 NATA admissions cycle. All of these are regulated by a single authority whose 2020 Minimum Standards of Architectural Education make no reference to AI. A comparative study of five major Indian schools and four

international programmes concluded that Indian architecture education has changed little over the past two decades and places less emphasis on emerging technologies than comparable programmes elsewhere (Jerome, Nair, and Thomas 2026). A separate survey of 100 students, academics and practitioners identified a pronounced gap between curricular content and the requirements of contemporary professional practice (Purohit and Sharma 2025).

This paper is structured around three central questions: How is AI reshaping the ways in which architecture is learned? How should institutions respond when students submit AI-generated work? And what concrete measures can Indian departments adopt in the short term? The second question receives the most extensive discussion, both because it is the primary concern of many teachers and because the research-based answer diverges from common expectations.

How this review was done This article presents a narrative, rather than systematic, review. Relevant studies were identified through searches of academic databases in fields such as architecture, design education, higher education, academic integrity and construction management. Search terms combined concepts including artificial intelligence, architecture education, design studio pedagogy, AI literacy, assessment design, academic honesty, AI detection and Indian higher education. Studies were selected on the basis of relevance, evidential strength and recency, with most published from 2022 onwards.

Three limitations should be noted. First, research on AI in architecture education remains at an early stage. Much of the available work is based on single institutions and small student cohorts, so quantitative findings require cautious interpretation. Second, no empirical studies were identified on AI use within Indian architecture schools. Evidence relating to India therefore derives from adjacent domains, especially medical education, where AI has been more extensively examined. Third, technological development is proceeding more rapidly than research. Conclusions about the capabilities of specific tools may already be outdated, whereas insights into pedagogy and institutional responses are likely to retain their relevance for longer.

Where Indian architecture education stands now Indian architecture education is overseen by a single central body with extensive authority over curriculum, admissions and staffing. This centralisation supports a degree of uniformity in standards across the country, but it also slows curricular change. Comparative analyses of Indian regulations and those in countries such as the United States and the United Kingdom show that Indian frameworks place relatively limited emphasis on new technologies and that there are discrepancies between regulatory provisions and institutional practice (Jerome, Nair, and Thomas 2026). In response, several authors have advocated a shift towards competency-based models (Kohale and Chakradeo 2024).

Pedagogical culture is at least as consequential as formal regulation. Indian architecture programmes are organised around the design studio, which carries the highest credit load

and is intended to integrate knowledge from all other subjects. In practice, this integration is often weak. A study of architectural history teaching found that historical content rarely appeared in students' studio work. The main reasons identified were modes of delivery, syllabus structure, language barriers and students' reluctance to transfer knowledge across modules (Sheoran and Garg 2025). AI is likely to follow a similar path: if it is confined to a separate elective, its systemic influence will remain limited.

The COVID-19 pandemic further exposed these patterns. When Indian architecture schools moved online in 2020, they handled the technical aspects of remote teaching relatively smoothly. Nevertheless, staff reported that online studios functioned poorly and that they required substantial training in how to teach design studio in this format (Varma and Jayasudha 2020). The implication is clear: installing new tools is comparatively straightforward, whereas transforming studio pedagogy is considerably more demanding. The central constraint is not technological access but the practice of teaching design.

At the policy level, the environment is broadly supportive. The National Education Policy 2020 positions technology as a means of enhancing access and quality and explicitly references AI. However, evaluations of its implementation repeatedly highlight three persistent issues: inadequate infrastructure, limited professional development for teachers and the absence of clear frameworks for data governance and ethics (Mondal 2026; Rehman, Ahmad, and Khan 2025). In summary, India currently has formal permission to engage with AI but lacks the capacity to do so effectively.

2. Where AI is showing up in the course

2.1 The design studio The strongest body of evidence concerns the early stages of design. In one study, 17 architecture students designed a cultural centre using Midjourney, Stable Diffusion and DALL-E. Image-generation tools enabled them to explore ideas they would not otherwise have encountered and helped sustain a more imaginative mindset, provided that design constraints were clearly articulated (Paananen, Oppenlaender, and Visuri 2023). A study in an interior design studio reported similar findings: AI expanded the range of options, accelerated iteration and clarified concepts through improved visualisations, although some students felt that the final outcomes no longer fully reflected their own authorship (Özdemir 2025).

Although there are fewer quantitative studies, they present a consistent picture. One investigation compared two studio cohorts comprising 162 students in total. The experimental group was permitted to use AI only for initial ideation and was required to document every prompt and version. Expert assessors judged their projects to be more creative; these students generated more ideas, completed more rounds of revision and produced work that was less homogeneous across the cohort, countering the common fear that AI leads to visual uniformity (He 2026). A much larger analysis of over four million artworks by more than 50,000 creators found that text-

to-image tools increased total output by roughly 25 per cent and raised the novelty of the most original ideas, while reducing average novelty and overall visual novelty (Zhou and Lee 2024). Collectively, these findings indicate that AI broadens the design space and accelerates exploration but contributes relatively little to selecting between alternatives.

Yet selection is central to architectural education. Across multiple studies, students report valuing AI less as projects progress. Following training workshops, architecture and interior design students expressed strong enthusiasm for image-based tools in early exploration but were more cautious once originality and evaluative judgement became central (Huh, Kim, and Park 2025). In a nine-week course, AI proved effective for architectural programming—the analytical, brief-formulation phase—but students struggled to control the final appearance of AI-generated designs, and their engagement with the tools was fragmented rather than systematic (Jin et al. 2024).

2.2 Building science and technical subjects AI is also entering technical subjects, albeit more quietly and in different forms. Here it is used primarily for computation rather than image generation. Machine learning models trained on simulation data can approximate building performance with accuracy approaching that of full simulations but in a fraction of the time, reducing calculation from weeks to days and enabling combined analysis of energy use, daylight, comfort and cost (Romaos, Mihalakakou, and Souliotis 2026; Shen, Pan, and Huang 2023).

These approaches are particularly pertinent to the Indian B.Arch, where building science and climatology are often taught using simple rules of thumb or a single software package. In one study, more than 200 second-year students with no prior experience of parametric tools were introduced to computational optimisation, and the method proved viable at that scale (Wang, Janssen and Ji, 2025). Two main issues emerged: students struggled to relate optimisation outputs back to their own design intentions, and the algorithm functioned as a “black box”, limiting conceptual understanding. These are pedagogical rather than technical challenges and will be familiar to staff who teach structures and building services.

2.3 Theory, history and written work Language models are most widely used in areas that typically receive less sustained attention from studio tutors: theory modules, research methods and dissertations. In the absence of architecture-specific data for India, the closest evidence comes from medicine. A review of Indian medical education studies reported that students were highly aware of AI and generally positive about it, but had received little formal instruction. They used AI tools to clarify difficult concepts, complete assignments and support self-directed study (Mateen et al. 2025).

Survey data indicate usage rates above 90 per cent, with primary concerns relating to accuracy and privacy, and a strong majority of students arguing that AI should be taught systematically within the curriculum (Bokan, Singh, and

Kumar 2026; Sorte, Tajne, and Bhagat 2025). A study of 1,211 students in India and Northern Ireland also found that attitudes towards AI were shaped far more by prior use than by background characteristics (Gerard, Lennon, and Bond 2024). This suggests that concrete experience, rather than abstract opinion, is the dimension of AI engagement most amenable to educational influence.

3. What AI does to learning

Individual empirical studies highlight both risks and benefits. A longitudinal investigation involving 494 students across three time points found that heavy workload and tight deadlines were associated with greater use of ChatGPT; higher use, in turn, was associated with increased procrastination, weaker memory and lower grades (Abbas, Jam, and Khan 2024). By contrast, an experiment with 125 students in a flipped research methods course reported substantial gains in critical, creative and reflective thinking (Essel et al. 2023). A further study with 213 students demonstrated that the depth of students’ engagement with AI was more consequential than their prior knowledge of such tools (Suriano et al. 2024). Research on cognitive offloading additionally indicates that the principal safeguard is students’ ability to evaluate the quality of AI-generated output (Jiang, Zhang, and Wang 2026).

The broader literature converges on a key conclusion: AI does not alter students’ thinking in a single, fixed manner. Its effects depend on how educators design learning tasks and regulate its use. A review of 67 studies conducted between 2022 and 2025 found that ChatGPT enhanced both critical and creative thinking when employed within structured, inquiry-based activities. Under loose, unstructured conditions, the same tool increased creativity but weakened critical thinking, and in some instances undermined both. This pattern was attributed to cognitive offloading, whereby students effectively allowed the system to do the thinking on their behalf (Li, Zhang, and Chen 2026).

In architecture education, these findings have a specific implication. High workload is structurally embedded in the design studio; it is not incidental. The Indian B.Arch programme, characterised by frequent submissions and sustained time pressure, reproduces the same risk conditions identified in these studies. The principal protective factor—students’ capacity to judge quality—is precisely what studio critiques are intended to cultivate. The danger is therefore greatest in the early years, before this evaluative judgement has fully developed.

4. The copying problem

What is really happening The main complaint in Indian architecture departments is straightforward: students are submitting work they did not create themselves. In one survey of 337 students, more than one-third reported using a chatbot for assessed work, and many did not regard this as cheating (Gruenhagen, Sinclair, and J.-A. 2024). This reframes how the problem should be understood. Frequently, students are not consciously violating a clear rule; rather, they are operating in

a grey area, replicating peers' behaviour and assuming that it is acceptable.

Architecture is particularly exposed for three main reasons. First, assessment is heavily focused on final products—drawings, renders, models and reports. Historically, these outputs were taken to imply a substantive design process; this assumption is no longer secure. Second, architectural work is highly visual, and contemporary image generators can now produce convincing presentation images within seconds. Early sketches that once served as evidence of authorship typically carry limited weight in grading. Third, written work—history essays, dissertations, thesis reports and building science assignments—is often judged solely on the final text submitted at a deadline. Empirical studies indicate that this assessment format is especially vulnerable in the context of widespread AI use (Kofinas and C.H.-H. 2025).

There is also more evidence than many departments recognise regarding the drivers of this behaviour. A review of 79 studies found that cheating declines when students seek to master the material, are intrinsically motivated and feel academically capable; it increases when they focus primarily on grades or experience low motivation (Krou, Fong, and Hoff 2020). Peer behaviour emerged as the strongest single influence across studies (Donse and de Boer 2013). Taken together with evidence that workload and deadline pressure drive students towards AI use (Abbas, Jam, and Khan 2024), this body of work directs attention back to assessment design. A course driven by grades, saturated with deadlines and judged only on final outputs renders copying a rational coping strategy.

5. What does not work

Four common institutional responses recur in Indian contexts, and the available evidence does not support any of them as a primary solution.

AI-detection software constitutes the first, and most harmful, response. A detailed study of fourteen detectors, including Turnitin, found that current tools are neither accurate nor reliable. They classify most text as human-written and fail when students simply paraphrase AI-generated output (Weber-Wulff et al. 2023). Another study of two commercial systems on a balanced set of texts reported accuracy scores of 0.61 and 0.69, with the weakest performance on mixed human–AI texts—the type most similar to real student work (Hadra, Alzubi, and Khalil 2026).

The fairness problem is even more serious, particularly in the Indian context. Detectors misclassify writing by non-native English speakers at much higher rates. One major study reported that 61.3 per cent of TOEFL essays were labelled as AI-generated, whereas essays by native speakers were almost never flagged (Liang et al. 2023). Subsequent work showed that even fluent or professionally edited English can trigger false positives (Park, Lee, and Kim 2026; Pratama 2025). Since most Indian architecture students write in a second or third language, systematic reliance on detectors would disproportionately penalise those least able to contest the result. The research consensus is clear: detector scores may

warrant further enquiry but cannot be treated as definitive proof (Van Vlasselaer, Deckers, and Peeters 2026; Dalalah and Dalalah 2023).

The second response is to rely on teacher judgement alone. Experiments at two UK universities showed that markers generally could not reliably distinguish which assignments involved AI and which did not. Moreover, merely suspecting AI use altered grading behaviour, leading to both false accusations and missed cases and thereby undermining fairness in both directions (Kofinas and C.H.-H. 2025). Challenging a student because work “seems” AI-generated thus constitutes conjecture rather than a defensible safeguard.

The third response is to impose a total ban on AI. Such bans have repeatedly failed: they push use underground, remove opportunities to teach responsible practice and do not eliminate the behaviour itself (Furze et al. 2024).

The fourth response is to rely exclusively on teaching academic honesty. A review of workshops and online modules found that they improved students' knowledge and stated attitudes but produced little clear change in behaviour (Stoesz and Eaton 2018). A study of a compulsory integrity course similarly yielded mixed and sometimes unexpected outcomes (Stephens et al. 2021). Integrity education is therefore necessary but insufficient on its own.

A further empirical finding contradicts widely circulated advice. Real-world, practice-based assessments are often promoted as the solution. However, when such tasks were systematically tested, AI systems generated realistic, contextually appropriate responses that experienced academics could not reliably distinguish from student work. Increasing the “authenticity” of the task did not make AI use easier to detect or prevent (Kofinas and C.H.-H. 2025). Realistic briefs are therefore not the principal answer; the critical requirement is to make the underlying design and learning processes observable.

6. What does work

Empirical research supports seven complementary strategies. These approaches are most effective when implemented in combination, and many already have precedents within architecture education.

- 6.1 State clearly how much AI each task permits The most effective shift is away from binary “allowed/banned” rules. The AI Assessment Scale specifies five levels of permitted AI use for each assignment, ranging from no AI to full AI, so that students know precisely what is allowed in each instance. A trial of this model reported fewer AI-related misconduct cases and higher student engagement (Furze et al. 2024). A related framework, developed from interviews with 61 teachers, categorises tasks into four groups: against AI, avoid AI, adopt AI and explore AI (Khlaif, Ayyoub, and Hamamra 2025). This aligns closely with studio practice: site analysis may fall at one level, concept generation at another and technical

drawings at a third. Hidden AI use is typically driven more by uncertainty than by explicit permission.

- 6.2 Assess the process as well as (or more than) the product If final written submissions alone cannot be regarded as reliable evidence of authorship, assessment must shift towards evaluating students' work processes (Kofinas and C.H.-H. 2025). Architecture has a structural advantage in this respect: crits, pin-ups, sketchbooks, interim reviews and oral examinations are already integral to every Indian B.Arch programme. What requires adjustment is the weight these forms of assessment carry in the overall grade. Evidence-based measures include requiring a record of prompts and iterations (He 2026), brief written reflections on process and oral justifications of design decisions (Kickbusch, Dawson, and Bearman 2025). A student explaining a structural bay or courtyard to a jury cannot delegate that explanation to AI.
- 6.3 Test the brief with AI before issuing it A review of guidance from the world's top fifty universities highlights a simple, yet still uncommon, practice: running the assignment through ChatGPT or an image model before issuing it to students and evaluating the quality of the resulting output (Moorhouse, Yeo, and Wan 2023). If a tool can generate a convincing response in 30 seconds, the issue lies with the assignment design rather than with student behaviour. In architecture, this points towards briefs grounded in real measurements, local climate data, user interviews, physical material tests and documented field visits—elements that AI cannot easily fabricate. The same review argues that the capacity to design such assessments now forms part of teachers' professional competence.
- 6.4 Make AI output the object of critique Rather than prohibiting AI, some studies position AI-generated output as material for critical analysis. In one experiment, students either used AI with structured critical reflection or used it without guidance. Those who engaged in structured reflection showed improvements in both technical and ethical dimensions (Martin, Smith, and Rubin 2025). In an architectural task involving 148 students, participants compared their own hand drawings of classical orders with AI-generated images of the same buildings. The AI images exhibited recurrent errors, and students identified a "hyperrealism" problem: the images appeared so polished that

errors were easy to overlook (Salazar Diaz, Rojas, and Vergara 2026). Tasks that require students to detect, analyse and explain such errors cannot be completed by AI on their behalf.

- 6.5 Reduce the pressures that drive copying Academic dishonesty tends to decrease when students prioritise learning over grades (Krou, Fong, and Hoff 2020), and to increase when they are overloaded and subject to intense deadline pressure (Abbas, Jam, and Khan 2024). Adjusting workload is therefore a strategy that serves both academic integrity and student wellbeing. For Indian architecture schools, this implies fewer submissions spaced further apart, allocation of marks to intermediate stages as well as final outputs, and assessment criteria that reward reasoning and developmental progress rather than sheet count or render quality. This dimension is rarely foregrounded in policy discussions, yet it is likely to be one of the most powerful levers available.
- 6.6 Develop a code of conduct jointly with students Three decades of research indicate that honour codes can reduce academic misconduct. They function through shared norms, transparent procedures and peer expectations rather than surveillance (Tatum 2022; Tatum and Schwartz 2017). Students who endorse their institution's code are substantially less likely to cheat, and peer behaviour continues to exert an independent influence (Bennett, Miller, and Rowe 2025). Given that classmates' behaviour is the strongest overall determinant, a concise code co-developed with students and renewed each year is likely to be more effective than a purely top-down policy.
- 6.7 Normalise declaring AI use The most practical definition of dishonesty in this context concerns whether AI use is concealed, rather than whether AI is used at all (Perkins 2023). A brief, mandatory declaration accompanying every submission—specifying which tools were used, when they were used and for what purposes—is straightforward to implement. Such a requirement normalises transparency, provides departments with valuable data and transforms an unenforceable ban into a rule that can be applied consistently. This declaration should appear alongside the reference list.

Table 1 links each common challenge to the response supported by research and to the response that should be avoided.

Table 1. Common problems, what the research supports, and what to avoid.

The problem	What works	What to avoid
Written work produced by AI (history papers, dissertations, reports)	Set a permission level for each task; require a declaration; ask students to defend the argument out loud; collect notes, outline and draft in stages	Using detection software as proof. It is unreliable and unfair to students writing in a second language

Presentation drawings generated rather than designed	Ask for the prompt and version log, concept sketches made before any AI image, and hand or physical development work	Accusing a student because the render looks too good. This distorts marking and creates false accusations
Students who do not know that undeclared use is cheating	State the permitted level for every task; write a departmental code with students; require a declaration on every submission	A blanket ban, which hides the behaviour and removes the chance to teach sensible use
Briefs that AI can answer well in seconds	Run each brief through the tools before issuing it; base tasks on site measurement, local climate data, fieldwork and community contact	Relying on realistic project briefs alone. AI produces realistic answers that fool experienced markers
Copying driven by deadlines and mark pressure	Fewer submissions, spread further apart; marks for intermediate stages; reward reasoning over sheet count	Adding more checking while leaving the workload exactly as it is
Teachers unsure what counts as acceptable use	Train staff in AI and assessment before anything reaches students	Letting individual teachers invent their own rules studio by studio

7. Problems specific to India

- The first challenge concerns unequal access. A survey of 215 participants in Indian higher education reported AI use at approximately 80 per cent in urban institutions but only around 45 per cent in rural institutions. Staff in rural colleges identified poor internet connectivity, weak infrastructure and a lack of training as the principal barriers (Srivastava and Sharma 2026). Analyses of Indian data similarly indicate that regions with fewer computers tend also to have fewer trained teachers, so shortages of equipment and expertise reinforce one another (Rawal 2024). AI image generation and cloud-based optimisation depend on adequate bandwidth and suitable devices. Institutions outside major urban centres are therefore likely to have constrained access, and their graduates may consequently develop different skill profiles.
- The second challenge relates to teacher preparedness. Interviews with Indian educators suggest that their understanding of AI is often shallow and oriented towards particular tools rather than underlying concepts. Many have limited hands-on experience, primarily use AI to automate routine tasks, and confront ethical questions without systematic training or institutional guidance (Kundu and Bej 2025). A review of assessment research reaches a similar conclusion, arguing that professional development in assessment, AI and digital literacy underpins all other reforms (Xia et al. 2024). Architecture staff face an additional difficulty because many are practising architects who trained before these tools existed. In this context, teacher training is not peripheral but central.
- The third challenge is regulatory silence. In the absence of clear guidance from the Council of Architecture, individual schools are compelled to improvise. International research indicates that such conditions typically lead students to use AI on their own terms and to withhold disclosure of that use (Ghonim, Eweda, and Elshater 2026). In a survey of the world's top fifty universities, just under half had issued any formal advice on AI and assessment (Moorhouse, Yeo, and Wan 2023). Indian architecture education lacks an equivalent framework. The construction sector faces a parallel situation: reviews describe fragmentation, weak data infrastructures and, in developing economies, low motivation, limited skills and cost barriers as major obstacles to adoption (Regona et al. 2022; Karthikesu, Rahman, and Ayer 2025).
- Bias, culture and ethics Bias in AI systems is not an abstract concern for Indian architecture; it is a daily pedagogical issue. Research on image-based tools in architecture highlights three levels of bias. Training datasets disproportionately represent English-language and Western material, the models promote particular aesthetic norms, and users' prompts and selections then reinforce these patterns in subsequent training cycles (Kudless 2023). When AI-generated façades were compared with how people actually perceive buildings, images based on location-specific prompts exhibited systematic distortions (Law, Seresinhe, and Shen 2025). A review of 58 studies confirms that benchmarks remain heavily Western and concludes that there is, at present, no reliable technical remedy for this imbalance (Elsharif, Alzubaidi, and Agus 2025).
- For a country with India's architectural diversity, the implications are immediate. A student requesting a courtyard house, a stepwell-inspired

public space, a jaali screen or a climate-responsive building in Kachchh or Kerala is querying a database in which such precedents are scarce and frequently stereotyped. Scholars have described this phenomenon as data colonialism, whereby AI defaults quietly embed Western assumptions into design imagery (de Almeida and Oliveira 2024). One study comparing AI-generated images of a city with its actual urban fabric found a narrow, commercially focused representation that could flatten cultural diversity if adopted uncritically (Campo-Ruiz 2025). For a discipline that purports to value regional and vernacular knowledge, this is a serious concern—but also a significant pedagogical opportunity. Asking students to compare AI-generated images with documented local buildings can render bias visible in ways that theoretical discussion alone cannot. Questions of authorship and copyright also remain unresolved, and teaching guidance on these issues is only beginning to emerge (Hedges 2024; Francis, Jones, and Smith 2025).

8. A year-by-year plan for the Indian B.Arch

- Four principles follow from this discussion, and none depends on prior regulatory action.
- First, AI should be embedded within the design studio rather than treated as a separate, peripheral

component. In one study, a twenty-hour AI skills module was integrated into studio teaching alongside ethics discussions. Students clearly preferred this approach to a standalone lecture-based course, and the module functioned effectively without altering the studio’s basic structure (Wang, Chen and Zhou, 2025). Given the typically weak connections between theory courses and studio work in Indian schools (Sheoran and Garg 2025), a separate AI elective is likely to be the least effective option.

- Second, AI should be introduced progressively, both by year level and by stage in the design process. This sequencing aligns with students’ own reports that AI is most helpful during early exploratory phases and substantially less useful as designs become more detailed (Huh, Kim, and Park 2025; Jin et al. 2024). Prompt-writing can be treated as a form of architectural language: studies indicate that students who formulated richer, more varied prompts obtained more open-ended and diverse outputs (Medel-Vera, án, and Rojas 2025; Lakousha, Ghonim, and Elshater 2026). Finally, the design process itself should become the primary focus of assessment. Table 2 illustrates how these principles can be operationalised across the five years of the programme.

Table 2. A staged plan for AI in the five-year B.Arch.

Year	What students learn	Where it happens	How it is checked
Year 1–2	How AI works, where its bias comes from, and what it cannot know	Basic Design and Architectural Design I–II; comparing AI images against measured drawings	Hand and physical work stays the main evidence; AI output allowed only as a marked-up critique
Year 2–3	Writing prompts as an architectural skill; questioning precedents; AI for early ideas only	Concept stage of design studio; construction precedent studies	Prompt and version log required; concept sketches dated before any AI imag
Year 3–4	Computational and performance methods; simulation shortcuts; parametric optimisation	Building Science and Climatology; climate-responsive studio; services	Simulation results explained and defended in viva; assumptions stated openly
Year 4–5	Judging AI output; authorship, ethics and disclosure; AI-assisted research writing	Thesis, dissertation, professional practice and research methods	Written declaration of AI use; process portfolio; oral defence of design decisions

Two preconditions are essential. First, teachers require targeted training before students begin using these tools. Such training must address pedagogical approaches and ethical considerations for teaching with AI, rather than focusing solely on software operation (Daher 2025; Xia et al. 2024). Second, each department needs a concise written policy

specifying when AI use is permitted and what students are required to disclose. This policy should differentiate between task types and be applied consistently across all studios. It is ambiguous rules, rather than explicit permission, that most strongly encourage concealed AI use (Perkins 2023; Furze et al. 2024).

What research India still needs The most salient finding of this review is an absence of empirical work: there are currently no data-based studies on AI use in Indian architecture education. Six strands of research are particularly needed.

First, a national baseline survey of architecture students and teachers in India. This should document their awareness of AI; how, when and for what purposes they use it; what they disclose; and what training they have received, disaggregated by region and institutional type.

Second, studio-based experiments with control groups that evaluate design quality through expert review rather than student self-report, and that test tiered AI-permission models in Indian studios.

Third, systematic evaluations of how AI tools represent Indian building traditions, regional typologies and climate-responsive design, generating material that can support both research and pedagogy.

Fourth, longitudinal studies examining whether early AI use affects freehand drawing, spatial imagination and understanding of construction. These issues constitute the primary concerns raised by teachers, yet there is currently no empirical evidence.

Fifth, accreditation-oriented research that links AI-related competencies to Council of Architecture standards.

Sixth, Indian replications of detector-bias studies using writing produced by Indian students, in order to demonstrate directly what international work already implies: that AI detection software cannot be deployed fairly in this context.

9. Conclusion

Overall, the evidence does not support either of the two dominant staff-room positions in Indian architecture schools. AI is neither a threat that can simply be excluded from the studio nor a straightforward mechanism for enhancing productivity. It is a tool that offers genuine benefits in the early stages of the design process, but its impact on students' judgement depends almost entirely on how teaching is structured around it.

With respect to copying, the evidence redirects attention away from conventional responses. Detection tools perform poorly and, in a context where many students write in a second language, are actively inequitable. Teachers cannot reliably identify AI-generated work through reading alone. Blanket bans are ineffective. Even realistic, practice-based briefs do not, by themselves, resolve the problem.

What appears to be effective is: specifying clearly the extent of permitted AI use for each task; grading process and live performance alongside the final output; designing briefs that AI cannot complete independently; requiring students to declare which tools they used; co-developing a code of conduct with students rather than imposing it unilaterally; and reducing workload and grade pressure so that copying ceases to be the rational choice. All of these measures are

immediately feasible for an Indian architecture department and none depends on acquiring new software.

India is currently characterised by permission without capacity. National policy encourages the adoption of new technologies, but the Council of Architecture's standards make no reference to them. Infrastructure and staff development vary widely across regions, while students are already advancing beyond both. The principal risk is not that Indian graduates will lack AI skills, but that they will employ AI without the capacity to critically evaluate its outputs, and that India's architectural diversity will be compressed into tools trained predominantly elsewhere.

The only element that will not emerge spontaneously is local evidence. Unless Indian schools undertake their own empirical studies, they will be guided primarily by findings from contexts such as Hangzhou, Riyadh, Oulu and Brisbane—valuable, but not equivalent to knowing what is occurring in Delhi, Chennai or Bhopal.

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