



From Constraints to Excellence: A Four-Stage Mentorship Model for IC Education in Private Universities

Xinxin Pan^{a*}, Benfu Jiang^b, Ziyang Cai^c, Fengquan Liu^d, Dongxv Xiao^e

School of Electronic and Information Engineering, Zhuhai College of Science and Technology, Zhuhai, China

^{a*}panxinxin@zcst.edu.cn, ^bford@zcst.edu.cn

^ccaiziyang@zcst.edu.cn, ^dlfq981111@163.com

^exdx170806@163.com

Abstract. Private application-oriented universities face three interconnected resource constraints in integrated circuit (IC) fabrication education: hardware constraints (limited TCAD tool licenses restrict research-oriented simulation for large student cohorts), faculty constraints (high student-to-faculty ratios make individualized instruction impractical), and knowledge capital constraints (limited research heritage makes every student output precious and in need of preservation). This paper proposes a three-component reform framework designed specifically for these resource-constrained settings: (1) a lightweight AI-assisted approach that uses machine learning surrogate models to bypass time-consuming TCAD simulations, achieving $R^2 > 0.97$ and over five orders of magnitude speedup; (2) a four-stage progressive pathway (“in-class → expansion → competition → academic outputs”) that serves as a cognitive scaffold—drawing on Vygotsky’s Zone of Proximal Development—to make research aspirations achievable step by step while concentrating limited faculty effort where it matters most; and (3) a cross-year mentorship cascade in which first-cohort students support second-cohort students as team members, amplifying faculty capacity and ensuring sustainable inheritance of scarce research outputs. Implemented over two years at a private university in China’s Greater Bay Area, the model produced tangible outcomes: 7 national and 17 provincial competition awards (from zero national awards before the association’s establishment in late 2023), 6 student-first-inventor layout designs, and 6 student first-author papers (3 accepted, 3 under review). This study provides a low-cost, replicable, and scalable reform paradigm for engineering education in resource-constrained private universities, offering actionable scarcity-driven insights for similar institutions worldwide.

Keywords: Engineering Education, Resource-Constrained Settings, IC Fabrication Course, AI for Science, Mentorship Cascade, Private Universities

1 Introduction

1.1 The Resource-Constrained Reality of Private Universities

Private application-oriented universities constitute a significant proportion of higher education institutions worldwide, yet they remain underrepresented in engineering education research. Unlike elite research universities that enjoy abundant funding, low student-to-faculty ratios, and deep research heritage, private universities typically operate under severe resource constraints that fundamentally shape what is pedagogically possible.

In the field of integrated circuit (IC) engineering education, these constraints are particularly acute. IC fabrication requires specialized software (Technology Computer-Aided Design, TCAD), computational resources, and faculty expertise—all of which are expensive and scarce in private university settings. Yet the strategic importance of IC talent cultivation, especially in regions like China's Greater Bay Area, demands that even resource-constrained institutions find effective ways to prepare students for industry careers.

1.2 Three Interconnected Resource Constraints

In our teaching practice at a private university in Zhuhai, China, we identified three interconnected resource constraints that hinder deep learning and research-oriented exploration in the Principles of Integrated Circuit Fabrication course.

Constraint 1: Hardware/Software Constraints — TCAD Licenses and Computational Efficiency

TCAD simulation is essential for understanding device physics and IC fabrication process optimization. However, private universities face a two-layer resource constraint in TCAD-based education.

The first constraint is substitutive. At elite institutions with cleanrooms, students fabricate physical devices and collect real data; TCAD simulations are used primarily to calibrate or validate experimental results. Private universities, by contrast, cannot afford cleanroom facilities. We therefore rely exclusively on TCAD simulations for both teaching and research—not as a supplement to real fabrication, but as its replacement.

The second constraint is quantitative. Even TCAD tools themselves are expensive. Commercial TCAD tools require costly licenses and significant computational resources. In our context, the number of concurrent licenses is limited, and each simulation—especially for advanced device models—can take hours to complete. As reported in the literature, a single 3D device simulation can take 14.5 hours and consume 48 GB of memory.

This creates a paradox: the course can support basic verification experiments (e.g., running pre-configured examples), but when motivated students attempt to conduct exploratory research—systematically varying parameters, testing novel structures, or op-

timizing designs—they face prohibitive computational wait times. The hardware constraint thus becomes a pedagogical bottleneck, limiting the depth of independent student inquiry.

Constraint 2: Faculty Constraints — High Student-to-Faculty Ratios and Limited Individualized Attention

Private universities typically enroll large cohorts with significant variation in student ability, prior preparation, and research interest. In our course, some students show strong motivation to explore beyond required content, while others struggle with basic concepts. Ideally, differentiated instruction would address this variation—providing enrichment for advanced students while supporting those who need remediation.

However, the student-to-faculty ratio in private universities makes individualized instruction impractical. Without graduate teaching assistants (a resource typically available only at research universities), a single faculty member must simultaneously manage course delivery, lab supervision, student mentoring, and research guidance. The result is that many motivated students receive insufficient support to translate their interest into tangible outcomes, a situation that has been studied in other resource-constrained educational settings ^[1].

Constraint 3: Knowledge Capital Constraints — Scarce Research Heritage and the Need for Preservation

Unlike research universities with established laboratories, publication records, and graduate student pipelines, private universities typically lack accumulated research heritage. Each competition award, each research paper, and each intellectual property registration is not routine output but a precious achievement—hard-won and potentially unrepeatable if not properly preserved.

This scarcity creates a distinctive challenge: how to ensure that the hard-earned knowledge, skills, and outputs of one student cohort are transmitted to the next? Without a systematic mechanism for knowledge preservation and transfer, each cohort starts from zero, and the institution fails to build cumulative capacity.

1.3 The IC Innovation Association as an Institutional Response

In late 2023, we established the IC Innovation Association, supported by the Guangdong Province IC Talent Training Base (awarded to our private university in 2022) and subsequent competitive government funding (RMB 8 million annually in 2024 and 2025). The association provides dedicated space, equipment, and a modest budget—not to eliminate resource constraints, but to create a platform for working within them.

1.4 Research Questions and Contributions

This paper asks: How can a private application-oriented university, operating under hardware, faculty, and knowledge capital constraints, design a sustainable mechanism to cultivate IC talent that produces verifiable research outputs?

We propose and validate a three-component reform framework, as summarized in Table 1.

Table 1. Three-Component Reform Framework

Components	Target Constraints	Core Ideas
Lightweight AI Empowerment	Hardware/Software	Use machine learning surrogate models to bypass time-consuming TCAD simulations, reducing computation from hours to milliseconds
Four-Stage Progressive Pathway	Faculty	Enable differentiated cultivation without individualized instruction through a staged “in-class → expansion → competition → academic outputs” pipeline
Cross-Year Mentorship Cascade	Knowledge Capital	First-cohort students support second-cohort students as team members, preserving and transmitting scarce research outputs

Figure 1 illustrates the complete problem-solution-outcome logic of the three-component reform framework.

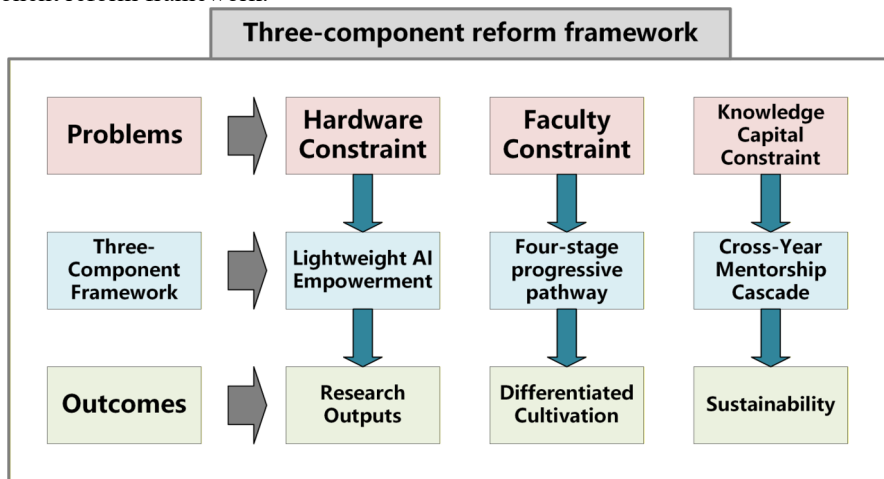


Fig. 1. The problem-solution-outcome logic of the three-component reform framework for resource-constrained private universities.

2 Theoretical Framework and Path Design

2.1 Resource-Constrained Innovation in Higher Education

The literature on innovation in resource-constrained settings (often called “frugal innovation” or “scarcity-driven innovation”) suggests that constraints can stimulate creative problem-solving rather than merely impeding progress. In engineering education, this perspective challenges the assumption that quality requires abundance.

Our study adopts this lens: we do not attempt to mimic elite research universities by acquiring more resources. Instead, we design mechanisms that work within constraint—bypassing computational bottlenecks (AI surrogates), structuring differentiated pathways (four-stage progression), and leveraging peer knowledge transfer (mentorship cascade).

2.2 AI for Science as a Strategic Direction

“AI for Science” has become a national strategic direction in China, aiming to use machine learning to solve computational bottlenecks in traditional scientific computing. In 2023, China’s Ministry of Science and Technology launched a special initiative on AI for Science^[2]. Recent studies have explored AI applications in engineering education, focusing on how generative AI can re-center student agency in design contexts^[3]. Our lightweight AI approach—using surrogate models to replace expensive simulations—operationalizes this concept at the undergraduate teaching level.

At resource-rich universities, students can fabricate physical devices and collect real data for advanced device research. But at our university, without a cleanroom, we lack access to real fabrication data. Moreover, even TCAD simulations—our only alternative—suffer from high computational costs and limited license availability. This constraint led us to explore AI surrogate models that learn the mapping from process parameters to device performance using simulation data. In other words, we use AI to bypass the hardware constraint—not by acquiring more resources, but by making the most of what we have.

3 The Three-Component Reform Framework

3.1 Component 1: Lightweight AI Empowerment — Bypassing Computational Bottlenecks

The Problem. Commercial TCAD simulations for advanced device structures (e.g., Gate-All-Around Tunnel FETs with quantum transport models) require hours per simulation. A student attempting to systematically explore parameter space—varying gate length, nanowire diameter, and oxide thickness—faces prohibitive wait times.

The Solution. Instead of acquiring more computational resources (which is expensive), we teach students to build machine learning surrogate models that learn the mapping from process parameters to device performance from a modest number of simulations. Once trained, these models predict performance in milliseconds—a speedup of over five orders of magnitude.

Technical Implementation. Students generated 216 structured simulation samples by varying three geometric parameters (gate length: 0.1–0.3 μm ; nanowire diameter: 0.05–0.09 μm ; oxide thickness: 0.003–0.007 μm) using a full factorial design. They evaluated four algorithms including Random Forest^[4] and selected Gradient Boosting Decision Tree (GBDT)^[5], which achieved $R^2 > 0.97$ for both threshold voltage (V_{th}) and saturation current (I_{dsat}) prediction. SHAP analysis confirmed that the model

learned physically consistent relationships (e.g., oxide thickness dominating V_{th} prediction) [6]. The technical implementation details have been validated in our prior work [7].

Resource Impact. This approach transforms a hardware constraint into a learning opportunity. Instead of waiting for simulations, students learn to think about experimental design, feature engineering, and model validation—skills directly transferable to industry AI roles. The integration of TCAD with AI for semiconductor design has been explored in industry contexts [8]. Low-cost approaches to engineering education—such as affordable electronic prototyping courses—have been shown to successfully achieve learning outcomes without expensive equipment [9].

3.2 Component 2: Four-Stage Progressive Pathway — Enabling Differentiated Cultivation Without Individualized Instruction

The Problem. With high student-to-faculty ratios, individualized instruction is impossible. Yet students vary significantly in ability and motivation. Moreover, in elite research universities, the academic environment itself provides implicit scaffolding: graduate teaching assistants, senior students, and a well-established research culture naturally show younger students how to move from coursework to research. For students in private universities, this scaffolding is absent. They may admire research outputs but have no concrete sense of how to reach them. The gap between “admiring research” and “doing research” remains a black box.

The Solution. We designed a four-stage progressive pathway that allows students to enter and exit at different points based on their readiness and interest, without requiring one-on-one faculty attention at every stage. Table 2 summarizes the pathway.

Table 2. Four-Stage Progressive Education Path Framework

Stage	Name	Core Activities	Student Role	Participation Scale
1	In-class Teaching	Basic theory + TCAD simulation	Knowledge acquisition	All enrolled students (100+)
2	Expansion	Literature review on Fin-FET, quantum transport, ML	Independent learning	Self-selected interested students (~30-40)
3	Competition	National IC Innovation Competition	Team-based project implementation	Motivated teams (~15-20 students)
4	Academic Outputs	Innovation training program + paper writing	Research deepening	High-achieving students (6-8)

How It Works Without Individualized Instruction.

Stage 1 is delivered through standard course instruction.

Stage 2 relies on self-directed learning—interested students are provided with curated literature and encouraged to form study groups. Faculty role is facilitation, not individualized tutoring.

Stage 3 uses competition deadlines as natural drivers. Students form teams and work autonomously; faculty provide occasional consultations.

Stage 4 involves the smallest group (6-8 students), where faculty can afford deeper engagement because the scale is contained.

Resource Impact (Faculty Perspective): The four-stage structure creates a natural filter. Only students who self-select and persist reach the stages requiring faculty attention. This is not “elite-only” cultivation—any student can progress if they demonstrate interest and capability—but it concentrates scarce faculty resources where they produce the highest marginal returns.

Student Perspective: Making the “How” Explicit. Beyond filtering, the pathway serves as a cognitive scaffold for students who aspire to research but lack a clear route. In elite universities, tacit knowledge about how to move from coursework to research is embedded in the environment. In private universities, that tacit knowledge must be made explicit. Stage 2 shows students what to read. Stage 3 shows them how to work on a project. Stage 4 shows them how to write a paper. Drawing on Vygotsky’s concept of the Zone of Proximal Development ^[11], each stage is designed to be within reach given the support available—peers in Stage 2, competition mentors in Stage 3, and faculty in Stage 4—so that students are continually challenged but not overwhelmed. The pathway thus transforms an abstract admiration of research outputs into a concrete, step-by-step journey.

Dual Function. From the faculty perspective, the pathway acts as a filter, concentrating scarce mentoring effort on the few students who reach Stage 4. From the student perspective, it acts as a ladder, making research aspirations achievable one stage at a time. This dual function—reducing faculty load while increasing student self-efficacy—is the core innovation of the four-stage design.

3.3 Component 3: Cross-Year Mentorship Cascade — Preserving and Transmitting Scarce Research Outputs

The Problem. Private universities lack the research heritage and graduate student pipelines of elite institutions. Each competition award, paper, or intellectual property registration is precious but vulnerable—without systematic preservation, it may not benefit future students.

The Solution. We established a cross-year mentorship cascade in which first-cohort students, having achieved research outputs, support second-cohort students as team members (not formal “mentors” in a hierarchical sense, but collaborators). Peer-to-peer active learning not only provides real-world context for junior students but also cements the engineering identity of senior students who serve as mentors ^[10]. The effectiveness of undergraduate peer mentors has been documented in course-based research experiences, where mentors also develop technical and interpersonal skills themselves. This cascade operates at three levels:

Level 1 (Faculty) directly mentors first-cohort students, serving as corresponding author on their papers and supervisor on their projects.

Level 2 (First-Cohort Students) who have achieved competition awards and research outputs join second-cohort projects as team members, providing technical support without assuming formal leadership roles.

Level 3 (Second-Cohort Students) benefit from this support while gradually building capacity to mentor future cohorts.

A Concrete Example of the Cascade in Action.

Student A (Class of 2021, First Cohort): In 2024, as team leader, he led his team to a national second prize. He has since published a first-author SCI paper (under review).

Student A → Student B (Class of 2023, Second Cohort): Student A joined Student B's national-level innovation training project as a team member, providing technical support. Student B became the project's principal investigator and has submitted a first-author EI paper to IEEE ICSICT (under review as of May 2026). The topic aligns closely with Student A's research.

Why "Team Member" Rather Than "Formal Mentor"? The cascade deliberately uses a flat "team member" role rather than a hierarchical "mentor" title. This lowers psychological barriers for second-cohort students (they are not being "taught" but "collaborated with") while allowing first-cohort students to contribute without excessive time commitment. The result is a low-cost, scalable knowledge transfer mechanism.

Resource Impact. The mentorship cascade addresses the knowledge capital constraint directly. Each output (competition award, paper, layout design) becomes not an endpoint but a seed for the next cohort. The cascade requires no additional budget—only a deliberate structural design that incentivizes cross-year collaboration.

4 Implementation and Evidence

4.1 Implementation Context

The framework was implemented at Zhuhai College of Science and Technology (ZCST), a private university in China's Greater Bay Area. The IC Innovation Association grew from 52 members in its first cohort (2024) to 83 members in its second cohort (2025)—a 59.6% increase, suggesting student-perceived value.

4.2 Quantitative Evidence: From Zero to Breakthrough

Table 3 presents the core quantitative indicators before and after the establishment of the IC Innovation Association. Competition awards are reported for the 2024 and 2025 cycles (the 2026 competition had not yet occurred at the time of writing). Intellectual property and paper outputs include outcomes through May 2026.

Table 3. Student Outcomes Before and After the Intervention

Indicator	Before Association (pre-late 2023)	After Association
National competition awards (all IC tracks)	0	7 (2024-2025)
Provincial competition awards	4	17 (2024-2025)
Registered layout designs (student first inventor)	0	6 (2024-2026)
Student first-author papers	1	6 (2024-2026: 3 accepted, 3 under review)

4.3 Case Studies: Three Resource Constraints in Action

Case 1: Student A and Student B — The Mentorship Cascade in Action (Addressing Faculty and Knowledge Capital Constraints)

Student A (first cohort) led his team to a national second prize in 2024 and has a first-author SCI paper under review. Rather than stopping there, he joined Student B’s (second cohort) national-level innovation project as a team member. Student B became the project’s principal investigator and has submitted a first-author EI paper. This cascade preserved Student A’s hard-won knowledge and transmitted it to Student B without requiring additional faculty time.

Case 2: Student C — From Basic Course to Graduate Research Aligned with the AI-for-Science Philosophy (Addressing Knowledge Capital Constraint)

Student C joined the association as a sophomore. In late 2023, under faculty supervision, he published a first-author EI-indexed paper on image recognition algorithms—demonstrating that even early-stage students can produce research outputs when given structured support. He later became the first inventor of a registered layout design (2025). While students from this course have pursued graduate studies before, his case is distinctive: he was admitted to a master’s program at the University of Macau Science and Technology, where his research focuses on wafer defect detection algorithms—a direct application of the AI-for-Science concept embedded in the course. He has also secured an invention patent in this area. His trajectory shows how the course reform can influence students’ long-term research directions, not merely increase the quantity of graduate admissions.

Case 3: Student D — Leadership and Typical Growth in the First Cohort

Student D joined the IC Innovation Association in 2024 and served as president of the first cohort. Starting from foundational IC knowledge, he progressed through the four-stage pathway while organizing peer activities and fostering the initial research

culture. In 2025, he became the first inventor of a registered layout design. In 2026, he published a first-author EI-indexed paper on LDO design and was hired as a layout engineer by Injoinic, a publicly listed IC company. His trajectory reflects both leadership development and a representative growth path under the proposed framework.

4.4 Summary of Evidence

Table 4 summarizes how the three components of our framework address each resource constraint and what evidence supports their effectiveness.

Table 4. Summary of Evidence Linking Constraints, Components, and Outcomes

Resource Constraint	How Framework Addresses It	Evidence
Hardware/Software (TCAD licenses, computation time)	Lightweight AI surrogate models ($R^2 > 0.97$, 5 orders speedup)	One student's paper on AI-accelerated TCAD simulation
Faculty (high student ratio, no TAs)	Four-stage progressive pathway (self-filtering, concentrated faculty attention at scale)	52→83 member growth, 7 national awards
Knowledge Capital (no re-search heritage, scarce outputs)	Cross-year mentorship cascade (first-cohort supports second-cohort)	Student A→Student B cascade, Student C's progression to graduate research

5 Discussion

5.1 Scarcity-Driven Excellence: A Counter-Narrative to Resource-Intensive Models

The dominant narrative in engineering education assumes that quality requires abundance—more funding, more equipment, more faculty, more graduate students. Our case offers a counter-narrative: resource constraints, when properly framed, can drive innovation in teaching and learning.

We term this “scarcity-driven excellence”—the deliberate design of educational mechanisms that work within constraints rather than attempting to eliminate them. The three components of our framework each exemplify this logic:

Lightweight AI works within computational constraints by bypassing rather than adding more simulations.

Four-stage progression works within faculty constraints by creating a self-filtering pipeline.

Mentorship cascade works within knowledge capital constraints by preserving and transmitting scarce outputs.

This narrative may be particularly relevant for the majority of higher education institutions worldwide—those that are not elite research universities but nevertheless must prepare students for technologically demanding industries.

5.2 Generalizability and Replicability

The framework's components are institutionally transferable:

Lightweight AI can be adapted to any engineering domain with computationally expensive simulations (e.g., fluid dynamics, structural analysis, electromagnetic modeling).

Four-stage progression can be applied to any course where student ability varies significantly and faculty resources are limited.

Mentorship cascade can be implemented in any extracurricular student organization, requiring only a deliberate structure that incentivizes cross-year collaboration.

5.3 Limitations

This study is a single-institution, single-course case study conducted at a private application-oriented university, which limits generalizability to other institutional contexts. Given the nature of curriculum reform in a single cohort and the constraints of real-world teaching, a strict experimental design with a control group and pre-post test measurements was not feasible. The evaluation relies primarily on longitudinal real-world outcomes, including competition awards, intellectual property, student publications, and representative case studies, rather than quantitative survey data or controlled comparisons. While these tangible outputs provide strong evidence of effectiveness, future work could include multi-institutional replication, expanded participant surveys, and more structured longitudinal assessments to further validate the proposed framework.

5.4 Implications for Practice

For faculty at resource-constrained institutions, our framework suggests three actionable strategies:

Teach students to build AI surrogates for expensive simulations rather than waiting for more computing resources.

Design staged pathways that allow students to self-select into deeper engagement without requiring individualized faculty attention at every level.

Structure cross-year collaboration explicitly—not as informal “mentorship” but as a designed mechanism where first-cohort students join second-cohort projects as team members.

6 Conclusion

This paper addressed a question largely ignored in the engineering education literature: how can a private application-oriented university, operating under hardware, faculty, and knowledge capital constraints, design a sustainable mechanism for IC talent cultivation that produces verifiable research outputs?

We proposed and validated a three-component framework specifically designed for resource-constrained settings: (1) lightweight AI empowerment that bypasses computational bottlenecks using machine learning surrogate models; (2) a four-stage progressive pathway that enables differentiated cultivation without individualized instruction; and (3) a cross-year mentorship cascade that preserves and transmits scarce research outputs.

Implemented over two years at a private university in China's Greater Bay Area, the framework produced tangible outcomes: 7 national and 17 provincial competition awards (from zero before 2023), 6 student-first-inventor layout designs, 6 student first-author papers.

We offer this framework not as a template to be copied mechanically, but as an illustration of what "scarcity-driven excellence" can look like in practice. For the many engineering educators working in resource-constrained settings—the majority of higher education institutions worldwide—we hope this case provides both inspiration and actionable strategies.

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