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Student Motivation and Research Interests in Engineering: Baseline Mixed-Methods Study to Design a Research-Based Learning Pathway

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Abstract*– Baseline evidence on student motivation and topic interests can inform the design of research-based learning (RBL) interventions in engineering education. This paper reports baseline findings from a mixed-methods study (survey N = 120; semi-structured interviews n = 10) conducted prior to implementing a longitudinal RBL pathway across three engineering mathematics courses in an Aerospace Engineering degree at Universitat Politècnica de València. Quantitative results indicate a high perceived value of early research-skills development (PVI = 4.70/5) and very high willingness to participate (95.8% rating 4–5), with motivation frequently attributed to the possibility of open-topic selection. Students reported broad interest in aerospace systems, AI/ML, sustainability, and telecommunications. Interview analysis yielded five themes: (1) research as an identity bridge from mathematical procedures to engineering practice; (2) scaffolding as an enabler despite high achievement; (3) time as the primary barrier; (4) traceability as professional practice; and (5) the need for clear boundaries for optional AI use. These findings inform the design of a two-year educational innovation project (PIME) that will implement staged deliverables, analytic rubrics, and postdoc-led student training sessions, and they motivate the planned evaluation framework for subsequent phases.

***Keywords*-- engineering mathematics; research skills; transferable modeling; assessment rubric; traceability.**

I. Introduction

Research-based learning (RBL) has gained prominence as a pedagogical approach for developing transferable competencies in engineering education. By engaging students in inquiry practices—formulating questions, evaluating evidence, justifying decisions, and communicating findings—RBL can help connect procedural knowledge with professional practice [1]. Designing RBL effectively, however, benefits from understanding students' motivations, interests, and perceived barriers prior to implementation. Without baseline evidence, even well-designed innovations may fail to align with what students value or with the constraints they anticipate.

In early engineering curricula, and particularly in engineering mathematics courses, a recurring issue is that students may develop strong procedural competence while still struggling to transfer mathematical thinking to open-ended problems that require explicit assumptions, model selection, and interpretation under uncertainty [2]. Traditional course structures can unintentionally position mathematics as a set of isolated techniques rather than as a language for modeling and reasoning about engineering systems. This perceived disconnect may weaken motivation and limits opportunities to practice competencies that matter in later coursework and professional contexts.

Prior work on undergraduate research and RBL suggests that early exposure to research experiences can contribute to research self-efficacy and research competence over time [4], [5], while engineering education literature emphasizes the importance of professional skills and identity development [3]. In parallel, innovation-oriented learning approaches aim to align STEM curricula with inquiry, creativity, and authentic problem-solving [6]. For early-stage students, key design questions remain: what topics and forms of inquiry are most motivating, what barriers are most salient, and what level and type of scaffolding is perceived as necessary to make participation feasible without reducing intellectual ownership.

This paper addresses these questions by reporting baseline evidence collected prior to implementing a longitudinal RBL pathway. Our goals are: (i) to characterize what motivates first-year aerospace engineering students to engage in research-oriented learning; (ii) to identify engineering topics that capture their interest; and (iii) to understand the scaffolding and support they perceive as necessary for successful participation. This baseline evidence informs the design of an educational innovation project (Proyecto de Innovación y Mejora Educativa, PIME) at Universitat Politècnica de València (UPV), which will implement the pathway across three consecutive engineering courses over two academic years (2025–2027).

The contribution of this paper is methodological and practical. Methodologically, we present a replicable mixed-methods baseline protocol combining survey and semi-structured interview data. By reporting evidence prior to performance outcomes, we aim to support transparent, evidence-driven educational innovation, clarifying what is established at baseline and what will be evaluated in subsequent phases.

II. Background and Content

A. Research-Based Learning in Engineering

RBL positions students as active participants in inquiry and knowledge construction rather than as passive recipients of information [1]. In engineering education, RBL commonly takes the form of open-ended projects in which students formulate a problem, select and justify methods, analyze information or data, and communicate findings—activities that resemble elements of professional engineering practice. Prior work suggests that sustained or longitudinal RBL experiences can support the development of transferable competencies such as autonomy, critical thinking, synthesis, and scientific communication [5].

When implemented progressively, RBL can be structured as a pathway that evolves from exploratory tasks to more analytical and method-driven projects, allowing students to increase ownership while receiving appropriate guidance as novices [6]. Evidence from undergraduate research and RBL studies indicates that research-oriented experiences may foster research competence and deeper engagement with disciplinary content when students perceive the tasks as meaningful and feasible [4], [5]. At the same time, implementation quality is sensitive to design choices: alignment between learning activities and assessment, the availability of timely feedback, and the level of scaffolding provided to novice researchers are often decisive for participation and sustained progress [2], [7]. At the same time, implementation quality is sensitive to design choices: alignment between learning activities and assessment, the availability of timely feedback, and the level of scaffolding provided to novice researchers are often decisive for participation and sustained progress.

B. The Role of Motivation in Research-Based Learning

Students select an open topic aligned with their interests, and student motivation is both a condition for engagement and a likely outcome of educational interventions. Intrinsic motivation—engagement driven by interest, curiosity, and personal meaning—has been consistently linked to deeper learning and sustained effort [8]. In RBL contexts, topic choice and perceived relevance are especially salient: students are more likely to persist when they can work on problems that connect to their interests and to recognizable engineering challenges [1], [8]. Motivation also interacts with perceived competence and support. Even highly motivated students may disengage if they lack research-enabling skills, such as narrowing scope, finding and evaluating sources, planning an approach, or managing information-literacy demands [9], or if feedback cycles are insufficient to help them course-correct [7]. Recent analyses of generative-AI assessment guidelines also emphasize the importance of clearly communicating acceptable use, academic-integrity expectations, and assessment design implications to students [10]. For these reasons, baseline evidence about motivation and perceived barriers can play a practical role in designing RBL pathways that are ambitious while remaining feasible.

C. Institutional Context: The PIME Framework

This study is situated within an educational innovation project (PIME/25-26/556) funded by the Instituto de Ciencias de la Educación (ICE) at UPV. The PIME framework supports structured educational improvement through projects with defined objectives, activities, evaluation plans, and dissemination strategies. The project, titled "Itinerario de Iniciación a la Investigación Matemática en el Grado de Ingeniería Aeroespacial", spans two academic years (2025–2027) and is embedded across three consecutive courses in the Aerospace Engineering curriculum: Mathematics I (first year, annual), Mathematics II (second year, first semester), and Advanced Mathematics for Aerospace Engineering (second year, second semester). The present paper reports baseline evidence collected prior to implementation to inform pathway design (e.g., topic interests, motivational drivers, perceived barriers, and support needs). Subsequent publications will report implementation and outcomes using performance and process indicators (e.g., participation, rubric-scored deliverables, and student perceptions tracked longitudinally across the two-year period).

III. Methods

A. Study Design

We employed a convergent mixed-methods baseline design combining a cohort-wide quantitative survey (N = 120) with semi-structured qualitative interviews (n = 10). The survey characterizes the distribution of attitudes and interests across the cohort, while interviews provide explanatory depth regarding motivations, perceived barriers, and design preferences for the planned pathway [11]. Data collection was conducted prior to implementation at the beginning of the academic year to inform intervention design and establish a pre-intervention reference point.

B. Participants and Setting

Participants were first-year students in the Aerospace Engineering degree program at Universitat Politècnica de València. The cohort (N = 120) reflects selective admissions and strong academic preparation in mathematics and sciences. The survey was administered to the full cohort during regular course time; 120 responses were obtained.

Interview participants (n = 10) were purposively selected to reflect diversity in topic interests and self-reported confidence, and to balance sex (5 men, 5 women). Data collection followed institutional ethics procedures. Survey responses were collected without identifying information for this baseline phase. Interview participants provided informed consent and were assigned pseudonymous identifiers (M1–M5 for men; F1–F5 for women).

C. Instruments

The survey included Likert-scale items (1 = strongly disagree; 5 = strongly agree) assessing perceived value of early research-skills development, willingness to participate, research self-efficacy, information-literacy comfort, attitudes toward optional AI support, and perceived barriers (e.g., time constraints). Multi-item constructs were summarized as composite indices computed as the mean of their constituent items: Perceived Value Index (PVI, 3 items), Perceived Need Index (PNI, 4 items), and Research Self-Efficacy (RSE, 5 items). Students also reported topic interests by selecting up to three areas from a predefined list. The semi-structured interview guide covered six sections: (1) background and interests, (2) perceived value and motivation, (3) design acceptability (deliverables, rubrics, traceability), (4) tools and AI, (5) barriers and feasibility, and (6) recommendations. Interviews lasted approximately 15–25 minutes and were conducted in person. Detailed field notes were taken during and immediately after each interview, including near-verbatim quotes when possible.

D. Analysis

Quantitative data were analyzed descriptively using means, standard deviations, and frequency distributions. To complement the descriptive analysis, exploratory associations among the main composite indices and selected single-item variables were examined using Spearman's rank correlations. For binary topic-interest variables, point-biserial correlations were used. Confidence intervals were computed via bootstrap with 2000 resamples. Given the baseline and design-oriented nature of the study, these analyses were interpreted as exploratory rather than as confirmatory hypothesis tests.

Qualitative data were analyzed using rapid thematic analysis guided by Braun and Clarke's reflexive thematic analysis framework [12]. First, two members of the research team independently reviewed the interview notes and highlighted meaningful segments related to motivation, perceived feasibility, scaffolding, AI use, and assessment preferences. Second, preliminary codes were grouped into candidate categories and compared across participants to identify recurrent patterns and divergent cases. Third, the research team discussed the candidate themes, refined their definitions, and checked them against the original notes for coherence, representativeness, and analytical distinctiveness. Representative quotations are reported to illustrate each theme. Because the qualitative component was intended to inform intervention design rather than to produce a full grounded theory, we prioritized thematic coherence, transparency, and design relevance over formal estimation of intercoder reliability.

IV. QUANTITATIVE FINDINGS

A. Perceived Value and Willingness to Participate

Students reported high perceived value for early research-skills development. The Perceived Value Index was 4.70/5 (SD = 0.42), as seen in Table I, indicating strong recognition that research competencies are important for their engineering education. Willingness to participate was exceptionally high: the single-item measure averaged 4.83/5 (SD = 0.48), with 95.8% of students rating willingness at 4 or 5 on the scale. These findings suggest a cohort receptive to research-oriented learning experiences. The Perceived Need Index was 4.01/5 (SD = 0.30), indicating that even this high-achieving cohort recognizes the need for structured support in translating mathematical competence into open-ended inquiry. Students' disposition to revise work after feedback was very high (4.47/5, SD = 0.22), supporting iterative design with multiple feedback cycles.

TABLE I

Summary of Baseline Survey Indices (N = 120)

Indicator	Mean	SD
Perceived Value Index (PVI)	4.70	0.42
Willingness to Participate	4.83	0.48
Perceived Need Index (PNI)	4.01	0.30
Revision Disposition	4.47	0.22
Research Self-Efficacy (RSE)	3.42	0.24
Time Constraint Barrier	3.21	0.65
AI Acceptance	4.12	0.58
Traceability Intent	4.33	0.31
Impostor-type concerns	2.57	0.25
AI Ethics Uncertainty	3.48	0.47

B. Topic Interests

Students expressed diverse interests in engineering challenges. The most frequently selected topic areas (shown in Table II) were aerospace/orbital systems and flight mechanics (65.0%) and AI/ML and data science (63.3%), followed by sustainability/environment (38.3%) and telecommunications / IoT (33.3%). This distribution supports the feasibility of an open-topic pathway that can accommodate heterogeneous interests.

TABLE II

Topic Interests (Select Up to Three; N = 120)

Topic Family	% Selected
Aerospace/Orbital & Flight	65.0%
AI/ML & Data Science	63.3%
Sustainability/Environment	38.3%
Telecommunications/IoT	33.3%
Logistics/Optimization	23.3%
Energy/Materials	22.5%
Biomedical/Health Technology	16.7%
Engineering education/innovation	11.7%

C. Barriers and AI Attitudes

Time constraints emerged as the primary feasibility concern. While the mean rating was moderate (3.21/5, SD =

0.65), 30.8% of students rated time constraints at 4–5, indicating a substantial subgroup for whom workload management will be critical. In contrast, impostor-type concerns were low (2.57/5), with only 12.5% rating this concern highly. Attitudes toward AI tools were notably bifurcated. Acceptance of AI as optional support was high (4.12/5, SD = 0.58), but uncertainty about acceptable or ethical use remained nontrivial (3.48/5, SD = 0.47). Traceability intent—willingness to document sources and decisions—was very high (4.33/5, SD = 0.31), suggesting students are receptive to transparency requirements.

D. Exploratory Associations among Baseline Variables

Table III reports exploratory associations among the main composite indices and selected single-item variables (N = 120). The associations generally supported the descriptive interpretation. Perceived value (PVI) showed a positive association with willingness to participate (ρ = .52, $p < .001$), suggesting that students who attributed greater importance to research-skill development were also more disposed to engage in the pathway. Research self-efficacy (RSE) showed a moderate positive association with willingness (ρ = .38, $p < .001$), indicating that students who felt more capable of conducting research were more inclined to participate. The time constraint barrier showed a weak negative association

with willingness (ρ = −.19, p = .037), consistent with the interview findings that identified workload management as a participation risk for a specific subgroup.

AI acceptance was positively associated with AI ethics uncertainty (ρ = .31, $p < .001$), suggesting that students may simultaneously value AI as a support tool and remain uncertain about its appropriate use. Traceability intent was also modestly associated with AI ethics uncertainty (ρ = .24, p = .008), indicating that students who are more attentive to documentation may also be more reflective about AI-related norms.

TABLE III
Exploratory Associations among Baseline Variables

Relationship	Association coefficient (95% CI)	p-value
PVI – Willingness to participate	.52 [.38, .64]	< .001
RSE – Willingness to participate	.38 [.21, .53]	< .001
Time constraint – Willingness to participate	–.19 [–.36, –.01]	.037
AI Acceptance – AI Ethics uncertainty	.31 [.14, .47]	< .001
Traceability Intent – AI Ethics uncertainty	.24 [.07, .40]	.008
Interest in AI/ML – RSE	.27 [.10, .43]	.003
Interest in AI/ML – Willingness	.22 [.04, .38]	.015
Interest in Aerospace – Willingness	.11 [–.07, .28]	.228

Note. Spearman's ρ is reported for continuous/ordinal pairs; point-biserial r is reported for binary topic-interest variables. Confidence intervals were computed via bootstrap with 2000 resamples. Given the exploratory nature of the analysis, p-values are interpreted descriptively.

Regarding topic interests, AI/ML interest was associated with higher RSE (r_{pb} = .27, p = .003) and willingness to participate (r_{pb} = .22, p = .015), whereas aerospace/orbital interest was not significantly associated with willingness (r_{pb} = .11, p = .228). Overall, these exploratory patterns suggest that motivation, perceived capability, topic interest, and feasibility concerns should be treated as related but distinct dimensions in the design of the pathway. Given the exploratory purpose of the analysis, p-values are interpreted descriptively rather than as confirmatory hypothesis tests.

V. Qualitative Findings: Thematic Analysis

Rapid thematic analysis of semi-structured interview notes (n = 10) identified five themes that clarify student motivation and feasibility constraints and directly inform pathway design. Each theme is summarized in Table IV and illustrated with selected quotations.

A. Theme 1: Research as identity bridge

Many students described the pathway as a way to connect procedural mathematics to engineering identity and practice. They emphasized that solving standard exercises differs from selecting models, stating assumptions, and justifying decisions in realistic engineering contexts.

> *"I can solve problems, but choosing what model to use and why is a different skill. If this pathway forces us to justify assumptions, that's exactly what I'm missing."* (M1)

Some participants also linked early research experience to reduced anxiety about later capstone-like work and to perceived career value (e.g., internships and applications), suggesting that framing the pathway as professional development may support engagement.

TABLE IV
Thematic Coding Framework

Theme	Description	Design Implication
1. Research as identity bridge	Students see RBL as connecting procedural math skills to engineering identity and practice	Frame pathway as professional development; emphasize transferable skills
2. Scaffolding as enabler	High-achieving students still need structure: templates, exemplars, clear scope	Provide roadmap templates, sample deliverables, topic-narrowing support
3. Time as primary barrier	Workload concerns dominate; students request predictable, small milestones	Staged deliverables; fast, rubric-aligned feedback; calendar-aware pacing
4. Traceability as practice	Documentation requirements seen as legitimate research practice, not bureaucracy	Integrate traceability checklist; frame as professional norm
5. AI boundary clarity	Students accept AI support but want explicit rules and documentation requirements	Explicit acceptable-use policy; disclosure as part of traceability

B. Theme 2: Scaffolding as enabler

Despite high achievement levels, students repeatedly requested structured supports: templates, exemplars, and guided scope definition. Open-topic choice was viewed as motivating, but feasibility and expectations were described as uncertain without concrete models.

> *"Open topic is exciting, but the hardest part is deciding what is feasible. I need a way to narrow it fast."* (F3)

This supports using early deliverables and exemplars as acceleration scaffolds (i.e., structure that enables ambition rather than remediation), especially during topic narrowing.

C. Theme 3: Time as primary barrier

Time constraints emerged as a salient feasibility risk. Students stressed that participation depends on a predictable pace and small milestones aligned with the semester calendar, particularly during exam periods.

> *"I'm in, but only if it's broken into small deliverables. If it's one big project, it will collide with exams and I'll drop it."* (M2)

They also associated sustained motivation with timely feedback that confirms whether work is on track before further investment, reinforcing the need for rapid, criterion-referenced feedback loops.

D. Theme 4: Traceability as Professional Practice

Students generally accepted documentation requirements when framed as authentic research and engineering practice rather than an administrative burden. Traceability was described as what separates defensible reasoning from unsupported opinion.

> *"The most valuable part is learning to justify decisions—assumptions, methods, limitations—like an engineer."* (F5)

This acceptance provides a foundation for implementing traceability checklists that document sources, record key decisions, and track revisions. The professional framing appears essential: students are more receptive when traceability is positioned as what researchers and engineers do rather than as compliance.

E. Theme 5: AI Boundary Clarity

Students were open to AI tools as optional support but requested explicit rules and documentation to ensure fairness and comparability across submissions. The emphasis was on clarity, not prohibition.

> *"I don't want ambiguity about AI. Tell us what is acceptable and how to document it, and then it's fair."* (F1)

Students suggested that AI use should be documented in the same manner as other sources, with explicit disclosure of what tools were used and how. This finding supports including an AI disclosure item in the traceability checklist and providing clear examples of acceptable use cases.

VI. Design Implications: The PIME Intervention

The following section presents design implications derived from the baseline findings and describes how they inform the PIME intervention (2025–2027). These implications should not be interpreted as evidence of intervention effectiveness, which will be assessed in subsequent phases of the project. Table V summarizes how the main qualitative themes translate into concrete design features and assessment choices.

A. Pathway Structure

The pathway spans three consecutive courses, each with increasing complexity. In Mathematics I, students select an open topic and submit a roadmap focused on problem framing, scope boundaries, assumptions/variables, and feasibility. In Mathematics II, they develop a structured draft including an analytical plan, supporting sources, and an initial traceability record. In Advanced Mathematics, they complete a final report emphasizing interpretation, limitations, and technical communication, complemented by an oral presentation with Q&A. Distributing milestones across courses is intended to reduce time-pressure peaks and support sustained engagement.

TABLE V

PIME Intervention Structure (2025–2027)

Course	Deliverable	Focus	Assessment
Mathematics I (Year 1)	Roadmap (1–2 pages)	Problem framing, scope, assumptions, feasibility	Rubric criteria 1–3; traceability checklist (planning-level)
Mathematics II (Year 2A)	Structured draft (4–5 pages)	Analytical methods, sources, initial results	Rubric criteria 1–5; traceability checklist
Advanced Math (Year 2B)	Final report + presentation	Interpretation, limitations, communication	Full rubric (6 criteria); oral Q&A

B. Scaffolding Components

To support open-topic inquiry without compromising comparability, the intervention includes: (i) exemplar deliverables across multiple topic domains (e.g., aerospace, AI/data, sustainability); (ii) a topic-narrowing worksheet; (iii) a shared analytic rubric (six criteria: problem formulation; variables/assumptions/context; mathematical approach; interpretation/limitations; source quality/evidence use; argumentation/clarity); and (iv) a traceability checklist to document links between key claims, sources, and documented decisions/iterations.

C. Postdoc-Led Training Sessions

Four short sessions (3–4 hours each), delivered by postdoctoral researchers, target research-enabling skills that students explicitly valued at baseline: (1) research methodology and scope definition; (2) ethics and integrity, including acceptable AI use and documentation; (3) bibliographic search, referencing, and reference-management workflows (given the moderate adoption rate observed at baseline); and (4) applied quantitative methods aligned with course level. These sessions are designed to reduce startup friction and standardize guidance across diverse topics.

D. Evaluation Plan

The PIME evaluation combines process indicators (participation, completion rates, tutoring attendance, and number of feedback iterations) with outcome indicators (rubric scores across staged artifacts, traceability checklist scores, and short perception surveys). Rubric scoring is performed by course instructors using a criterion-referenced approach; postdoctoral staff support training delivery and data reporting. This design enables testing whether high baseline motivation translates into sustained engagement and measurable gains once artifact-based assessment data become available.

VII. Discussion

A. Interpreting Baseline Motivation

Across methods, baseline data indicate strong receptivity to research-oriented learning in this cohort. High perceived value (PVI = 4.70/5) and willingness to participate (95.8% rating 4–5) are consistent with interview accounts in which students framed research skills as a bridge between procedural mathematics and professional engineering practice. At the same time, students' requests for structure suggest that motivation alone is insufficient: scaffolding is perceived as an enabler of agency by reducing uncertainty about scope, expectations, and quality criteria. This interpretation aligns with formative assessment perspectives emphasizing the role of clear criteria and actionable feedback in supporting self-regulated learning.

B. Topic Interests and Design Fit

Interest patterns (aerospace systems, AI/ML, sustainability, telecommunications/IoT) reflect the multidisciplinary landscape of aerospace engineering. These distributions support an open-topic pathway, provided that assessment remains comparable across heterogeneous projects. Practically, this implies that exemplars and templates should span multiple domains and that the rubric should foreground transferable competencies (problem framing, assumptions/variables, method justification, interpretation/limitations) rather than domain-specific content.

C. Feasibility: Time Constraints as the Primary Risk

Time was the dominant barrier for a substantial subgroup (30.8% rating time constraints 4–5). This motivates friction-reducing design choices: small staged milestones, fast rubric-aligned feedback, and explicit calendar integration. In this baseline phase, these are design hypotheses; their adequacy will be evaluated using behavioral indicators (participation, completion, iterations) and artifact-based scoring in subsequent phases.

D. Limitations

This study has several limitations. First, it reports baseline perceptions collected before the implementation of the RBL pathway; therefore, stated motivation and willingness to participate may not persist under real course constraints. Second, the selective nature of the cohort limits generalizability. First-year Aerospace Engineering students at UPV typically enter with strong mathematics and science preparation, and their interest profile may be shaped by the disciplinary identity of aerospace engineering, where topics such as orbital systems, flight mechanics, AI, and sustainability are especially salient. As a result, the high baseline motivation observed here should not be assumed to generalize directly to less selective cohorts, to students with weaker mathematical preparation, or to engineering programs with different disciplinary orientations.

The qualitative component also has limitations. Although interview participants were purposively selected to reflect variation in topic interests, confidence, and sex, the small interview sample (n = 10) may not capture the full range of student perspectives, especially those of students less inclined to participate in research-oriented activities. Finally, because the baseline measures are largely self-reported, subsequent phases of the project will triangulate student perceptions with participation data, completion rates, feedback iterations, traceability records, and rubric-scored artifacts. Nevertheless, the design logic may be transferable: before implementing RBL pathways in other contexts, instructors should collect local baseline evidence on student interests, perceived barriers, and support needs, and adapt the scaffolding, exemplars, and assessment rubric accordingly.

E. Implications for Practice

Baseline evidence supports two implications: (i) even high-achieving cohorts benefit from scaffolding framed as acceleration/quality assurance, and (ii) explicit AI-use rules plus documentation address fairness concerns and reinforce transparency as a professional norm. These design choices will be tested during implementation.

VIII. Conclusion

This paper reports baseline evidence collected before implementing a longitudinal research-based learning pathway embedded in aerospace engineering mathematics. Survey data (N = 120) show very high perceived value and willingness to participate, while interviews (n = 10) highlight five design-relevant themes: RBL as a bridge to engineering identity, scaffolding as an enabler, time as the main barrier, traceability as professional practice, and the need for clear AI-use boundaries. These findings directly shape the 2025–2027

PIME design (staged deliverables, rubric, traceability checklist, and targeted training). Next, we will shift from perceptions to implementation evidence by tracking participation/fidelity and scoring student artifacts to test for measurable competency gains.

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