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An Immersive Digital Twin Workflow for Engineering Education Using Reality Capture, Virtual Reality, and Additive Manufacturing

Brian Warren, Opeyemi Ojajuni

Department of Mechanical Engineering, Southern University and A&M College, Baton Rouge, LA, USA
Email: Brian.warren@sus.edu

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Abstract

The growing adoption of digital twins, reality capture, virtual reality (VR), and additive manufacturing in industry has created a need for engineering education approaches that integrate these technologies within authentic learning experiences. This study investigates the educational effectiveness of a Physical-to-Digital-to-Physical (PDP) learning framework that engages students in the complete workflow of reality capture, digital twin creation, immersive visualization, and physical fabrication. A quasi-experimental study was conducted with 68 undergraduate engineering students enrolled in an introductory engineering course. Students in the PDP group ($n = 46$) participated in a semester-long experiential learning workflow involving LiDAR scanning, point cloud processing, digital modeling, VR interaction, and 3D printing, while a control group ($n = 22$) received conventional instruction. Student outcomes were evaluated using course grades, pass rates, retention measures, and attendance-related failures. Results indicate that the PDP framework significantly improved academic performance and student engagement. PDP students achieved higher pass rates (87.0% vs. 63.6%), more favorable grade distributions ($\chi^2(5) = 13.98$, $p = 0.016$), and eliminated attendance-related failures. The intervention was particularly effective for academically at-risk students, substantially increasing the likelihood of successful course completion. These findings suggest that immersive, experiential learning environments that position students as creators of digital twins rather than consumers of prebuilt models can enhance learning, engagement, and persistence in engineering education. The study provides evidence that integrating reality capture, digital twins, VR, and additive manufacturing within a unified instructional framework offers a promising approach for preparing students for emerging digital engineering workflows and Industry 4.0 environments.

Keywords

Digital Twins, Engineering Education, Reality Capture, Virtual Reality, Additive Manufacturing, Experiential Learning, Immersive Learning

1. Introduction

The convergence of digital twin technology, reality capture systems, virtual reality (VR), and additive manufacturing (AM) is fundamentally restructuring the competency expectations of professional engineering practice. These technologies collectively enable the creation, interrogation, and physical realization of high-fidelity digital representations of real-world systems constituting the operational backbone of Industry 4.0 and cyber-physical production environments. The pace of this transformation is reflected in market projections: the global digital twin market, valued at approximately $13.6 billion in 2024, is forecast to exceed $119 billion by 2029 at a compound annual growth rate of 45.7% [1], while the broader Industry 4.0 technology sector is projected to reach $1.6 trillion by 2030 [2]. Yet the workforce pipeline required to sustain this expansion is critically underprepared.

A landmark study by Deloitte and The Manufacturing Institute projects that the U.S. manufacturing skills gap could leave as many as 2.1 million jobs unfilled by 2030, at a potential cost to the national economy of $1 trillion in that year alone, with digital skills identified as the fastest-growing unmet competency requirement [3]. A 2024 update to that study further projects 1.9 million skilled manufacturing positions remaining unfilled if current talent development trajectories are not corrected, with attracting and retaining digitally skilled talent cited as the primary business challenge by 65% of surveyed manufacturers [4]. Against this backdrop, the adequacy of existing engineering education frameworks to produce graduates fluent in digital twin workflows, immersive visualization, and additive fabrication has become a matter of significant institutional and economic urgency.

Digital twins have emerged as a central instrument of this technological shift, enabling dynamic, continuously updated virtual representations of physical assets across their full operational lifecycle. Advances in reality capture, encompassing terrestrial LiDAR scanning, structured light systems, and photogrammetric techniques, have made it possible to generate high-accuracy digital models from physical environments with unprecedented speed and precision. These capabilities are increasingly coupled with immersive VR technologies that support intuitive visualization and spatial interaction with complex engineering systems, and with additive manufacturing platforms that close the loop from digital model back to physical artifact. Taken together, these technologies define a continuous Physical-to-Digital-to-Physical (PDP) workflow that directly mirrors the design, simulation, and fabrication pipelines now standard in leading engineering practice.

Engineering education has responded to these developments through increased emphasis on experiential learning, project-based instruction, and the integration of emerging digital technologies. Research has demonstrated educational benefits associated with digital twins, virtual reality, reality capture, and additive manufacturing, including improvements in systems thinking, spatial reasoning, engagement, and design competency. However, these technologies are typically implemented as standalone instructional tools rather than as components of an integrated learning ecosystem. As a result, students often interact with pre-developed digital content instead of actively participating in its creation.

This represents a significant gap in the literature. While the educational value of each technology has been examined independently, limited research has investigated learning outcomes within a unified Physical-to-Digital-to-Physical (PDP) workflow that integrates reality capture, digital twin development, immersive interaction, and physical fabrication. Consequently, little is known about how engaging students as creators throughout the entire digital engineering process influences academic performance, engagement, retention, and success among academically at-risk learners.

This study addresses that gap by investigating a PDP instructional framework that integrates reality capture, digital twin construction, virtual reality interaction, and additive manufacturing within a single experiential learning environment implemented in an introductory engineering course across two academic semesters. Unlike previous approaches that position students primarily as consumers of digital content, the proposed framework engages students as creators throughout the entire digital engineering workflow.

The study evaluates the educational effectiveness of this framework through a quasi-experimental two-group design (N = 68) and is guided by three research questions:

- RQ1: How does the integration of a PDP learning framework affect student academic performance in engineering education compared with traditional instructional methods?
- RQ2: To what extent does the PDP learning framework improve student engagement and course retention in undergraduate engineering courses?
- RQ3: How effective is the PDP instructional workflow in supporting experiential learning and improving pass rates among academically at-risk engineering students?

The remainder of this paper is organized as follows. Section II reviews the relevant literature and theoretical foundations. Section III describes the methodology and PDP workflow implementation. Section IV presents quantitative results. Section V provides discussion, implications, and limitations. Section VI presents conclusions and future research directions.

2. Literature Review

The rapid convergence of digital twin technologies, reality capture systems, Virtual Reality (VR), and Additive Manufacturing (AM) is reshaping how engineers design, analyze, and interact with physical systems. Among these technologies, digital twins have emerged as a transformative paradigm for creating dynamic virtual representations of physical assets throughout their lifecycle [5]-[7]. Originally introduced by Grieves within the context of product lifecycle management, digital twins have since been adopted across manufacturing, aerospace, healthcare, and infrastructure sectors [6]. As industry increasingly embraces digital transformation, engineering education faces growing pressure to prepare students with the skills required to navigate these interconnected digital ecosystems. Recognizing this need, researchers have begun exploring digital twins as educational tools capable of providing students with access to systems and environments that may otherwise be inaccessible because of cost, scale, complexity, or safety considerations [8] [9].

Evidence suggests that digital twin-based learning environments can improve educational outcomes. For example, Nikolakis *et al.* [10] reported measurable improvements in task accuracy and procedural retention among students trained using digital twin systems compared to conventional instructional approaches. These findings support the growing belief that immersive and interactive digital representations can enhance engineering education by making abstract concepts more tangible and accessible. However, most existing studies position students as consumers of prebuilt digital twins rather than active creators. In these implementations, learners interact with completed models that have already undergone data acquisition, processing, and visualization stages, limiting opportunities to engage with the underlying technologies and workflows that drive digital twin development.

At the same time, advances in reality capture technologies have expanded opportunities for creating highly accurate digital representations of physical objects and environments. Techniques such as terrestrial LiDAR scanning, photogrammetry, structured-light scanning, and depth-camera sensing generate dense point cloud datasets that serve as the foundation for digital twin construction [11]. These technologies are increasingly utilized in fields such as geomatics, civil engineering, and archaeology [12], where students gain exposure to modern methods of documenting and analyzing real-world environments. Beyond simple data collection, point cloud processing requires students to engage with complex concepts involving coordinate systems, geometric reconstruction, noise filtering, registration, and mesh generation. Industry-standard software platforms such as Autodesk ReCap, Leica Cyclone, CloudCompare, and MeshLab provide powerful environments for performing these tasks while simultaneously exposing students to workflows widely used in reverse engineering, quality inspection, and as-built documentation. Despite the educational value of these activities, existing studies have largely focused on the application of processed datasets, with limited attention given to student engagement with raw scanning data and the complete transformation of physical reality into interactive digital assets.

Developments in immersive technologies have further expanded the educational potential of digital representations. Research examining VR in higher education consistently demonstrates benefits related to spatial understanding, learner engagement, motivation, and knowledge transfer [13]. Within engineering education, VR has been successfully applied to virtual laboratories, structural visualization, safety training, and assembly planning. Studies have demonstrated significant positive effects of VR-based learning on STEM outcomes, identifying enhanced spatial reasoning, computational thinking, learner engagement, retention, and knowledge transfer as key mechanisms underlying these improvements [14]-[17].

Yet a common characteristic of these implementations is that students interact with environments and models created by instructors, researchers, or software developers. Consequently, learners often remain disconnected from the processes through which virtual environments are generated, limiting opportunities for deeper ownership and construction of knowledge. Similarly, additive manufacturing has become an established component of engineering curricula, primarily serving as a tool for rapid prototyping, design validation, and experiential learning [18]-[21].

Educational research has demonstrated that transforming digital designs into physical artifacts enhances engagement, motivation, and design self-efficacy while helping students translate abstract concepts into tangible forms. Moreover, interaction with self-fabricated prototypes has been shown to deepen understanding of geometry, dimensional accuracy, and assembly tolerances beyond what digital environments alone can provide. However, additive manufacturing is typically taught as an isolated activity rather than as part of a broader digital engineering workflow. As a result, students often encounter fabrication as a final output rather than as a component of a continuous Physical-to-Digital-to-Physical (PDP) process connecting reality capture, digital twins, immersive visualization, and physical production.

The educational potential of integrating these technologies is supported by established learning theories. Kolb's Experiential Learning Theory (ELT) [22] argues that effective learning occurs through a cyclical process involving concrete experience, reflective observation, abstract conceptualization, and active experimentation. Likewise, constructivist perspectives in STEM education emphasize that knowledge is most effectively developed through active creation, authentic problem solving, and collaboration. Combined with experiential learning theory, these perspectives suggest that a PDP learning cycle, where students capture physical objects, construct digital twins, interact with them in immersive environments, and return them to the physical world through fabrication, can foster deeper understanding, systems thinking, and meaningful knowledge construction.

Despite substantial progress across digital twin research, reality capture education, VR-enhanced learning, and additive manufacturing pedagogy, these domains have largely evolved in parallel rather than as an integrated educational ecosystem. Existing studies have examined digital twins as instructional tools, reality capture as a technical skill, VR as a medium for visualization and simulation, and additive manufacturing as a prototyping platform. However, little research has investigated a unified workflow in which students actively participate in the entire process from physical data acquisition and point cloud generation to digital twin construction, immersive VR interaction, and physical reproduction through additive manufacturing. More importantly, the educational implications of positioning students as creators rather than consumers throughout this end-to-end pipeline remain largely unexplored.

This gap is particularly significant because it shifts the learner's role from interacting with pre-constructed artifacts to constructing, manipulating, and validating digital representations derived from physical reality. The present study addresses this gap by investigating a comprehensive Physical-to-Digital-to-Physical (PDP) workflow that integrates reality capture, digital twin creation, virtual reality interaction, and additive manufacturing within a single experiential learning framework.

3. Methodology

3.1. The Physical-to-Digital-to-Physical Education Intervention

The Physical-to-Digital-to-Physical Workflow was implemented as a structured five-stage laboratory project integrated into the regular engineering curriculum, as seen in Figure 1.

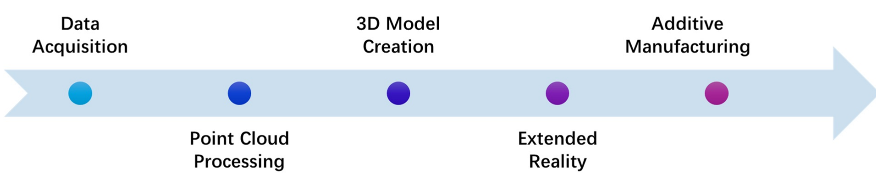

Figure 1. Physical-to-digital-to-physical workflow.

The Physical-to-Digital-to-Physical (PDP) Workflow was implemented as a semester-long experiential learning intervention designed to immerse students in a complete digital engineering pipeline. Working in teams of four, students began by performing reality capture of selected campus architectural structures using a Leica RTC360 3D laser scanner. The scanner collected high-resolution spatial data through LiDAR technology and HDR imaging, enabling students to document real-world environments and generate accurate digital representations.

Students then processed the raw point cloud data using industry-standard software, including Leica Cyclone REGISTER 360, Leica Cyclone 3DR, and CloudCompare. During this stage, students learned to remove noise, align multiple scans, register datasets, and create unified point cloud models. These activities introduced fundamental concepts in spatial data processing, coordinate systems, and digital reconstruction workflows commonly used in engineering practice.

Following point cloud processing, students transformed the scanned data into structured three-dimensional models using Autodesk Revit and Blender. Point clouds were converted into mesh-based representations, and HDR texture mapping was applied to enhance visual realism. This phase exposed students to Building Information Modeling (BIM), computer-aided design (CAD), and digital twin development while reinforcing the relationship between physical structures and their virtual counterparts.

The resulting models were exported as FBX files and integrated into virtual reality environments developed in Unity using the OpenXR framework. Students explored and interacted with their self-generated digital twins using Meta Quest 2 head-mounted displays and a CAVE immersive visualization system. These environments supported collaborative review, design modification, and spatial analysis, allowing students to experience engineering models at full scale and engage in iterative design activities within immersive settings.

The final stage of the workflow extended the digital experience back into the physical world through additive manufacturing. After completing VR-based reviews and design refinements, students prepared their models for fabrication using MakerBot 3D printers. Fabricated components underwent post-processing and dimensional inspection using digital calipers, with measured dimensions compared against the original scan data and CAD specifications.

This final activity established a feedback loop between physical and digital representations, enabling students to evaluate model accuracy, understand manufacturing constraints, and reinforce the connection between reality capture, digital modeling, immersive visualization, and physical production.

Collectively, the PDP Workflow provided students with an end-to-end learning experience that integrated reality capture, digital twin creation, virtual reality, and additive manufacturing within a single educational framework. By actively engaging students in each stage of the process, the intervention emphasized experiential learning, systems thinking, and the practical application of emerging digital engineering technologies.

3.2. Research Design

This study employed a quasi-experimental research design to investigate the educational impact of a Physical-to-Digital-to-Physical (PDP) instructional framework on student learning outcomes in an introductory engineering course (ENGR120). The PDP framework integrated reality capture technologies, point cloud processing, immersive virtual reality (VR), and additive manufacturing into a hands-on engineering learning environment.

3.3. Hypothesis Testing Framework

The formal null and alternative hypotheses corresponding to each research question are stated below in Table 1. This structure ensures transparency regarding the inferential claims tested and the basis on which each hypothesis is evaluated.

Table 1. Research questions and corresponding hypotheses.

	Hypothesis	Statement
RQ1	H_{10} (Null)	There is no statistically significant difference in overall course grade distribution between students in the PDP instructional group and those in the conventional instruction group.
	H_{11} (Alternative)	Students in the PDP instructional group demonstrate a significantly more favorable distribution of final course grades than students receiving conventional instruction.
RQ2	H_{20} (Null)	The rate of course non-completion (F, FN, and W grades) does not differ significantly between the PDP and conventional instruction groups.
	H_{21} (Alternative)	Students in the PDP instructional group exhibit a significantly lower rate of course non-completion than those in the conventional instruction group.
RQ2	H_{30} (Null)	The pass rate (grades A, B, or C) among academically at-risk students does not differ between the PDP and conventional instruction groups.
	H_{31} (Alternative)	Academically at-risk students in the PDP instructional group achieve a significantly higher pass rate than their counterparts in the conventional instruction group.

3.4. Participant

Sixty-eight engineering students (N = 68) enrolled in a freshman engineering course participated in the study during the Spring and Fall 2024 semesters. The PDP group (n = 46) received instruction through the Physical-to-Digital-to-Physical workflow, while the control group (n = 22) received conventional instruction consisting of CAD exercises, textbook-based learning, and traditional prototyping. Students remained in their assigned course sections, resulting in a quasi-experimental design that preserved ecological validity [33]. Both groups were drawn from the same introductory engineering course (ENGR 120) at the same institution and were required to meet the same enrollment prerequisites. The course content, learning objectives, and grading standards remained consistent across semesters. However, institutional records did not contain prior cumulative GPA or prerequisite course grades for all students, making it impossible to statistically compare the academic backgrounds of the two groups before the intervention. In addition, no formal matching process was used to ensure the groups were equivalent at baseline. As a result, differences in factors such as prior academic preparation, motivation, or students' choice of enrollment semester may have influenced the outcomes observed in this study. These limitations are discussed further in the Discussion section, and the findings should be interpreted with caution because complete baseline equivalence data were not available.

3.5. Data Collection

Data were collected from 68 undergraduate engineering students and included final course grades categorized as A, B, C, F, Failure due to Non-attendance (FN), and Withdrawal (W). Grades of A, B, and C were classified as passing outcomes, while F, FN, and W were classified as non-passing outcomes. Grade categories with no observations (D and NR) were excluded from analysis. The FN designation was treated as an indicator of severe disengagement, reflecting students who ceased course participation entirely.

3.6. Data Analysis

Quantitative statistical analyses were conducted to compare academic outcomes between the PDP and control groups. Descriptive statistics were first used to summarize grade distributions, pass rates, failure rates, and attendance-related outcomes across both semesters. Inferential statistical methods were subsequently applied to evaluate the significance of observed differences between instructional groups. A Pearson chi-square test of independence was used to analyze differences in overall grade distributions between the PDP and control groups. To further examine binary academic outcomes, a Fisher's Exact Test was conducted using pass versus non-pass classifications. Effect size measurements were additionally computed to evaluate the practical significance of the findings. A post hoc power analysis was also performed to assess statistical robustness. All statistical analyses were conducted using a significance threshold of $\alpha = 0.05$. The combined analytical approach enabled both statistical and practical evaluation of the educational effectiveness of the PDP learning framework in engineering education.

3.7. Operationalization of Outcome Constructs

To ensure clarity in interpreting the results, the three primary outcome constructs (academic performance, student engagement, and course retention) are operationally defined here as distinct, non-overlapping measures corresponding to the study's three research questions.

Academic performance (RQ1) refers to the distribution of final course grades across the full categorical scale (A, B, C, F, FN, and W). This construct captures the quality of learning achievement across the full grade spectrum and serves as the primary indicator of instructional effectiveness. It is assessed via the Pearson chi-square test of independence applied to grade frequency distributions across both instructional groups.

Student engagement (RQ2, first component) is operationalized narrowly as course attendance behavior, indexed by the institutional designation of Failure due to Non-Attendance (FN). The FN grade is assigned when a student ceases active course participation entirely and is therefore treated as a behavioral indicator of severe disengagement rather than academic underperformance. It is distinct from an earned failing grade (F), which reflects continued participation with insufficient academic achievement. Engagement is evaluated via Fisher's Exact Test comparing FN rates between groups.

Course retention (RQ2, second component) is operationalized as successful course completion, defined as receiving a final grade of A, B, or C. Non-completion encompasses all outcomes that preclude credit attainment: earned failures

(F), attendance-based failures (FN), and voluntary withdrawals (W). While related to engagement, retention is treated as a separate construct because it captures the combined effect of disengagement, academic difficulty, and voluntary attrition—factors that may operate independently. Retention is evaluated via Fisher's Exact Test on binary pass/non-pass classifications.

These three constructs are reported as sequential but conceptually distinct outcomes. Readers should note that a student who receives an FN is also counted as non-passing in the retention analysis; accordingly, the engagement and retention comparisons are not statistically independent. This overlap is explicitly acknowledged in the Results and Discussion sections.

4. Results

This section presents the quantitative findings from 68 ENGR 120 students enrolled during the Spring and Fall 2024 semesters. Of these students, 46 participated in the Physical-to-Digital-to-Physical (PDP) instructional workflow, while 22 received conventional instruction. Analyses were conducted to examine differences in academic performance, student engagement, and retention, and outcomes among academically at-risk students. Statistical significance was evaluated at $\alpha = 0.05$ using SPSS Statistics (v28) and Python (SciPy v1.11).

A preliminary examination of student outcomes revealed a consistent advantage for students participating in the PDP workflow. Across both semesters, 87.0% of PDP students (40 of 46) earned passing grades (A, B, or C), compared with 63.6% of students in the control group (14 of 22), representing a 23.4 percentage-point difference in favor of the PDP intervention as seen in Figure 2.

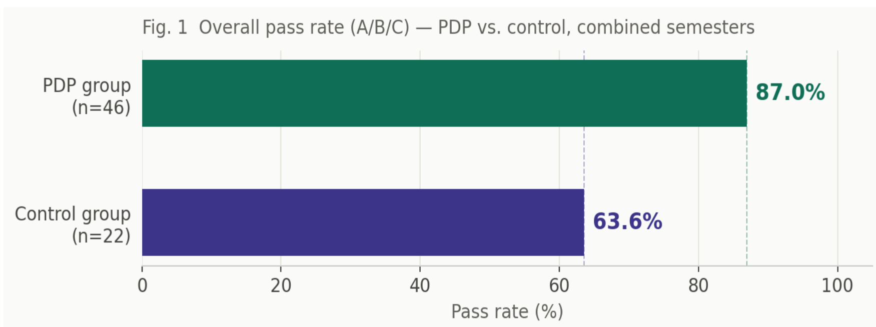

Figure 2. Overall pass rate (A/B/C)—PDP vs. control group, combined semesters.

Across all three research questions, the evidence converged on a consistent pattern favoring the PDP instructional framework as seen in Table 2. Students participating in the PDP workflow achieved significantly better overall grade distributions, experienced complete elimination of non-attendance failures, and demonstrated substantially higher success rates among academically at-risk learners. Although the overall course-completion comparison narrowly missed conventional statistical significance, effect-size estimates and power analysis indicate that the observed advantage was practically meaningful and likely constrained by sample size limitations. Collectively, the findings provide strong evidence that integrating reality capture, digital twin development, virtual reality, and additive manufacturing within a unified PDP workflow can positively influence student achievement, engagement, and persistence in engineering education. The RQ3 at-risk subgroup was identified post hoc based on final grade outcomes (C or below) rather than prospectively before the intervention. Results for RQ3 should be treated as exploratory and hypothesis-generating. RR = Relative Risk; Res. = adjusted standardized residual from chi-square analysis.

Table 2. Summary of hypothesis testing outcomes.

H	RQ	Key Test	Result	Decision	Effect
H_1	RQ1	Pearson $\chi^2(5)$	p = 0.016	Reject H_{10}	V = 0.454
H_2	RQ2	Fisher's Exact (FN)	p = 0.011	Reject H_{20}	FN = 0% PDP
H_2	RQ2	Fisher's Exact (Pass/Fail)	p = 0.051	Fail to Reject*	OR = 3.81
H_3	RQ3	Residuals + Relative Risk	Res. = +2.02/−2.89; RR = 4.30×	Support H_{31}	RR = 4.30

The findings demonstrate that the PDP learning framework significantly improved academic performance compared with conventional instruction. Students in the PDP group achieved a significantly more favorable grade distribution, with an overall pass rate of 87.0% compared to 63.6% for the control group. Statistical analysis confirmed a significant difference between groups ($\chi^2(5) = 13.98$, p = 0.016), with a large effect size (Cramér's V = 0.454). The results support the alternative hypothesis (H_{11}) and reject the null hypothesis (H_{10}), indicating that the PDP instructional framework produced significantly better academic outcomes than conventional instruction. Students who participated in the PDP workflow achieved a more favorable distribution of final course grades, with a significantly higher pass rate and a large effect size. These findings suggest that integrating reality capture, XR visualization, and additive manufacturing into engineering education can enhance student learning and improve overall academic performance.

The second research question investigated whether participation in the PDP workflow improved student engagement and course retention. Engagement was assessed through Failure due to Non-Attendance (FN), while retention was evaluated using overall course non-completion rates (F, FN, and W combined). The findings provide partial support for H_{21}, indicating that the PDP workflow positively influenced student engagement and retention. No students in the PDP group received a Failure due to Non-Attendance (FN) grade, compared to four students in the control group, a statistically significant difference (p = 0.011). Additionally, the PDP group exhibited a substantially lower non-completion rate (13.0% vs. 36.4%), and students were nearly four times more likely to complete the course successfully (OR = 3.81). Although the overall non-completion comparison narrowly missed statistical significance (p = 0.051), the findings suggest that immersive interaction with scan-derived digital twins enhances student engagement, reduces disengagement, and promotes course persistence.

The third research question explored outcomes among students whose final grades placed them near the pass-fail boundary. Because this subgroup was identified retrospectively from final grade distributions, the analysis should be considered exploratory rather than confirmatory. Within this subgroup, 78.3% of PDP students earned a passing grade (C or above), compared with 22.2% of control-group students, corresponding to a relative risk of 4.30. Standardized residuals also indicated a significant concentration of passing outcomes within the PDP group. This pattern suggests that the PDP framework may provide additional support for students at greater academic risk, helping more students achieve course completion. However, because at-risk students were not identified before the intervention, these findings should be viewed as hypothesis-generating. Future research should prospectively identify and track at-risk learners to determine whether PDP-based instruction can reliably improve outcomes for students near the pass-fail threshold.

The pass/non-pass comparison yielded a borderline result ($p = 0.051$), prompting a post-hoc power analysis to evaluate whether sample size limitations influenced the findings. The analysis revealed a statistical power of 60.4%, below the recommended 80% threshold, indicating that the study was underpowered to reliably detect the observed effect. Based on the observed pass-rate difference (23.4 percentage points), approximately 108 participants would have been required to achieve adequate power, representing a shortfall of about 40 students. These results suggest that the near-significant finding may reflect limited statistical power and an increased risk of Type II error, rather than the absence of a meaningful difference between the PDP and control groups.

5. Discussion, Recommendation, and Future Direction

The findings provide consistent evidence that the Physical-to-Digital-to-Physical (PDP) learning framework positively influences academic performance, student engagement, and support for academically at-risk learners in engineering education, as seen in Table 3.

Table 3. Summary of key findings.

RQ	Key Finding	Interpretation
RQ1	PDP students achieved a higher pass rate (87.0%) than control students (63.6%).	The PDP workflow significantly improved academic performance and was particularly effective in helping students near the pass-fail threshold to achieve passing grades.
RQ2	No PDP student received an FN (Failure due to Non-Attendance) grade, compared to 18.2% of control students. PDP students were also more likely to complete the course.	Immersive interaction with self-generated digital twins were associated with higher engagement, reduced disengagement, and improved course retention.
RQ2	78.3% of at-risk PDP students achieved a passing grade compared to 22.2% of at-risk control students.	The PDP workflow was particularly effective in supporting borderline students, helping convert potential failures into successful course completion.

Students participating in the PDP workflow achieved significantly better grade outcomes than those receiving conventional instruction, with a higher overall pass rate (87.0% vs. 63.6%) and a statistically significant difference in grade distribution ($\chi^2(5) = 13.98$, $p = 0.016$; Cramér's $V = 0.454$). Importantly, the intervention's strongest effect occurred at the pass-fail boundary, where students who might otherwise have failed were more likely to achieve passing grades. This finding suggests that the PDP workflow functions less as an accelerator for high-performing students and more as a mechanism for supporting learners with marginal understanding.

The results also demonstrate a substantial engagement benefit. No student in the PDP group received a Failure due to Non-Attendance (FN) grade, compared with 18.2% of students in the control group. This finding indicates that immersive, hands-on learning activities involving reality capture, digital twin creation, virtual reality, and additive manufacturing can strengthen student motivation, participation, and persistence. Although the broader non-completion comparison narrowly missed conventional statistical significance ($p = 0.051$), the large odds ratio ($OR = 3.81$) and post-hoc power analysis suggest that the observed difference likely reflects a meaningful educational effect that warrants further investigation with larger samples.

The exploratory analysis for RQ3 suggests that the PDP framework may be particularly beneficial for students near the pass-fail threshold. Although the at-risk subgroup was identified retrospectively and therefore does not support confirmatory conclusions, students in the PDP group achieved passing grades at substantially higher rates than comparable students in the control group (78.3% vs. 22.2%). This pattern is consistent with the possibility that the iterative, multimodal nature of the PDP cycle provides additional cognitive and motivational support for students with marginal understanding. However, because at-risk status was not established before the intervention, this interpretation remains tentative. Future research should prospectively identify academically at-risk students using measures such as prior GPA, placement scores, or early course performance and examine whether PDP-based instruction differentially improves outcomes for this population.

From a theoretical perspective, the study provides empirical support for Kolb's Experiential Learning Theory and constructivist learning principles. The sequential workflow of scanning, processing, modeling, virtual interaction, and fabrication creates repeated opportunities for students to move between concrete and abstract forms of learning. Practically, the findings indicate that PDP-based instruction may serve as an effective strategy for improving retention, reducing disengagement, and strengthening workforce-relevant competencies in digital engineering technologies. The framework also aligns with engineering accreditation objectives by integrating problem-solving, experimentation, digital tools, and project-based learning within a single instructional experience.

Based on these findings, engineering programs should consider integrating reality capture, digital twins, virtual reality, and additive manufacturing into introductory engineering curricula. Particular emphasis should be placed on early-semester hands-on activities and structured reflection opportunities to maximize student engagement and learning. Future research should focus on adequately powered multi-institutional studies, randomized or matched experimental designs, prospective identification of at-risk students, and longitudinal assessments of learning retention. Additional work is also needed to evaluate lower-cost implementations, measure outcomes such as spatial reasoning and digital modeling proficiency, and assess the long-term cost-effectiveness of PDP adoption.

This study was limited by its quasi-experimental design, small sample size, and the lack of comprehensive baseline academic data, which restricted the ability to fully account for selection effects. In addition, the use of final course grades as the primary outcome measure and the focus on a single course at one institution may limit generalizability. Future research should employ larger samples, collect baseline measures such as prior GPA and prerequisite performance, and examine PDP implementation across multiple courses and institutions. Despite these limitations, the positive outcomes observed suggest that the PDP framework is a promising approach for enhancing student learning and engagement through immersive, experiential education.

6. Conclusions

Engineering education is evolving as new technologies such as digital twins, virtual reality, and advanced manufacturing become increasingly important in industry. However, many engineering courses still rely heavily on lectures and textbooks. The PDP workflow presented in this study offers a different approach by allowing students to actively create and interact with engineering systems rather than simply learning about them. Students scanned real buildings, created digital models, explored them in virtual reality, and produced physical prototypes through 3D printing. The results suggest that this hands-on learning approach improved academic performance, increased student engagement, and helped struggling students succeed at higher rates than traditional instruction.

While these findings are promising, additional research with larger and more diverse student populations is needed to confirm the results. Nevertheless, this study provides an important foundation for future work by demonstrating how emerging technologies can be integrated into engineering education in a meaningful and practical way. As engineering programs continue to prepare students for a technology-driven workforce, the PDP framework offers a promising model for creating more engaging, immersive, and effective learning experiences.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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