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C-SMART: An AI-Driven Lidar and XR Framework for Automated Construction Monitoring and Engineering Education

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Abstract:

Rapid advancements in robotic LiDAR, artificial intelligence (AI), and immersive technologies are transforming how construction professionals collect, interpret, and apply spatial data for decision-making. However, the systematic integration of these technologies into construction engineering education remains limited. To address this gap, this paper introduces C-SMART (Construction Sustainability, Monitoring, and Automated Reality-capture Technique), an AI-driven educational framework that bridges automation research with experiential learning in engineering programs. C-SMART integrates robotic, terrestrial, and mobile LiDAR data collection, machine learning–based point cloud processing, and immersive visualization to support automated as-built modeling and scan-to-BIM analysis within a modular instructional pipeline designed to mirror end-to-end industry workflows. Beyond technical integration, the educational design of C-SMART emphasizes clearly defined learning outcomes related to automation literacy, spatial reasoning, and systems-level understanding. These outcomes are explicitly aligned with ABET student outcomes and ACCE competencies to support accreditation requirements. While the framework is informed by prior instructional experience with its individual components, this paper outlines a planned pilot implementation within an upper-level course and a mixed-methods assessment strategy, including pre- and post-module evaluation, to measure learning effectiveness. By emphasizing pedagogical grounding and a technology-agnostic approach focused on workflow reasoning rather than specific hardware, C-SMART contributes a scalable educational model for preparing construction engineers to operate in data-driven, automated, and sustainability-focused professional environments.

1. *Introduction:*

The construction industry is undergoing a rapid digital transformation driven by advances in reality-capture technologies, artificial intelligence (AI), and immersive visualization platforms (Lee & Arjmand, 2026; Prabhakaran et al., 2025). Robotic, terrestrial, and mobile LiDAR systems now enable the continuous collection of high-resolution three-dimensional (3D) spatial data, supporting applications such as automated progress monitoring, quality control, safety analysis, and sustainability assessment (Arjmand et al., 2023; Jafari, Melika, 2022). In parallel, AI-based point cloud processing and digital-twin environments are increasingly used in industry to automate as-built modeling and compare constructed conditions against design intent (Arjmand et al., 2026; Pan et al., 2022; Panahi et al., 2023). While these technologies are becoming integral to modern construction practice, their systematic integration into construction engineering education remains limited (Davila Delgado et al., 2020).

Construction engineering curricula have traditionally introduced emerging digital tools through isolated courses or stand-alone laboratory exercises, such as surveying and geomatics labs, building information modeling (BIM) courses, or construction management software modules. Although these approaches expose students to individual technologies, they often fail to convey how data collection, automation, analysis, and visualization are integrated within real construction workflows. As a result, students may graduate with familiarity in specific tools but without a holistic understanding of automated monitoring systems, closed-loop decision-making, or the interdisciplinary coordination required for digital construction environments. This disconnect between rapidly evolving industry practices and educational preparation poses challenges for workforce readiness, particularly in areas related to automation, data-driven decision-making, and sustainability-focused project delivery (Alshayeb et al., 2026; Dotta Correa et al., 2025).

Recent studies in engineering education have emphasized the importance of experiential and systems-based learning to prepare students for complex, technology-rich professional environments (Tembrevilla et al., 2024). In the context of construction engineering, this includes engaging students with real-world spatial datasets, automation pipelines, and collaborative digital platforms that mirror industry practice (Kurzinski et al., 2022) . However, implementing such experiences at scale presents several challenges, including the coordination of interdisciplinary content, access to advanced sensing technologies, integration across multiple courses, and the development of meaningful assessment strategies that go beyond software proficiency. There is a clear need for educational frameworks that connect reality capture, AI-driven analysis, and immersive visualization into coherent learning experiences that can be implemented within existing curricula (Kurzinski et al., 2022).

To address this need, this paper introduces C-SMART (Construction Sustainability, Monitoring, and Automated Reality-capture Technique), an AI-driven educational framework designed to integrate LiDAR-based reality capture, automated point cloud processing, and extended/mixed reality (XR/MR) visualization into construction engineering education. Rather than presenting C-SMART solely as a technical system, this work frames it as a modular educational platform that supports experiential learning across civil, construction, geomatics, architectural, and mechanical engineering contexts. The framework enables students to engage with the full lifecycle of digital construction data, from autonomous or semi-autonomous data acquisition, to AI-based feature extraction and semantic classification, to immersive visualization and interpretation within scan-to-BIM and digital-twin environments.

The educational design of C-SMART emphasizes clearly defined learning outcomes related to automation literacy, spatial data interpretation, interdisciplinary collaboration, and sustainability-informed decision-making. The framework is informed by prior instructional and research experience with reality capture, point cloud processing, and digital construction workflows that have been applied independently in undergraduate and graduate coursework. These experiences shaped the modular structure of C-SMART and its alignment with existing course objectives, supporting feasibility for future classroom integration without major curricular restructuring.

The contributions of this paper are threefold. First, it presents an integrated educational framework that bridges AI, LiDAR, and immersive technologies within construction engineering curricula. Second, it articulates a pedagogically grounded structure for incorporating automation-focused workflows into existing courses while emphasizing systems thinking and engineering judgment. Third, it discusses anticipated educational outcomes, implementation considerations, and future directions for formal classroom deployment and assessment. By focusing on educational design alongside technical integration, this work aims to support educators seeking to prepare the next generation of construction engineers for data-driven, automated, and sustainable industry practices.

2. *Background and Related Work*

2.1. *Digital Construction Technologies in Engineering Education*

Over the past decade, construction engineering education has increasingly incorporated digital tools to reflect evolving industry practices (Besiktepe et al., 2024) . Lidar-based reality capture has been introduced in surveying and geomatics courses to support spatial data collection and 3D modeling, while building information modeling (BIM) platforms are commonly taught in construction management and design coordination contexts (Mutis & Antonenko, 2022). More recently, artificial intelligence (AI) and machine learning techniques have begun to appear in graduate-level coursework and research-oriented classes, particularly for applications such as automated object detection, point cloud classification, and progress monitoring. Immersive technologies, including virtual, augmented, and mixed reality (VR/AR/MR), have also been explored as visualization and training tools for construction safety, sequencing, and design review (Ogunseiju et al., 2021).

Despite these advancements, the use of digital technologies in construction engineering education has largely remained tool-centric and compartmentalized (Besiktepe et al., 2024). Reality capture, BIM, AI-based analysis, and immersive visualization are often taught in isolation, with limited emphasis on how these components interact within automated construction workflows. As a result, students may gain proficiency in individual software environments or sensing techniques without developing an integrated understanding of how spatial data are collected, processed, analyzed, and used to inform construction decision-making. This fragmented exposure contrasts with industry practice, where data-driven automation increasingly relies on interconnected systems rather than stand-alone tools (Din et al., 2024).

2.2. *Experiential and Systems-Based Learning Approaches*

Engineering education research has consistently highlighted the value of experiential, project-based, and systems-oriented learning for preparing students to address complex real-world problems (Tembrevilla et al., 2024). In construction engineering, experiential learning has been shown to improve student engagement and conceptual understanding by connecting theoretical knowledge to practical applications, such as site-based projects, case studies, and collaborative design exercises (Kurzinski et al., 2022). Systems-based learning further emphasizes the interactions between technical components, organizational processes, and stakeholder roles, aligning well with the interdisciplinary nature of construction projects (Prince & Felder, 2006).

Several studies have explored the use of project-based learning and real-world datasets to enhance student understanding of construction processes. However, implementing such approaches with advanced digital technologies introduces additional challenges, including the coordination of interdisciplinary content across courses, access to high-quality spatial data, integration of automation concepts into existing curricula, and the development of assessment strategies that evaluate more than software operation skills (Tembrevilla et al., 2024). Without a structured framework, experiential activities risk becoming isolated demonstrations rather than cohesive learning experiences that support long-term competency development (Prince & Felder, 2006).

2.3. *Need for Integrated Educational Frameworks*

The growing complexity of digital construction environments highlights the need for educational frameworks that explicitly integrate reality capture, AI-driven analysis, and immersive visualization into unified learning experiences (Besiktepe et al., 2024). Such frameworks should enable students to understand not only individual technologies but also the end-to-end workflows that support automated monitoring, quality control, and sustainability assessment in practice. Moreover, effective frameworks must be pedagogically grounded, scalable within academic programs, and supported by clear learning objectives and assessment methods (Tembrevilla et al., 2024).

While prior work has demonstrated the educational potential of LiDAR, BIM, AI, and XR individually, there remains a gap in construction engineering education for platforms that connect these components into a coherent, automation-focused learning ecosystem (Kurzinski et al., 2022). Addressing this gap requires moving beyond isolated technology adoption toward integrated educational models that reflect the interconnected nature of modern construction systems. This need motivates the development of the C-SMART framework described in the following section.

Prior educational implementations at other institutions have demonstrated the feasibility of incorporating reality capture (Kurzinski et al., 2022), UAV-based data acquisition (Mutis & Antonenko, 2022), and digital construction technologies (Besiktepe et al., 2024) into construction curricula. The C-SMART framework builds upon these efforts by integrating AI-driven automation and immersive visualization into a unified, end-to-end educational workflow. Unlike prior implementations that focus primarily on individual technologies or isolated course modules, C-SMART explicitly integrates reality capture, AI-driven automation, scan-to-BIM analysis, and immersive visualization within a unified instructional pipeline designed to mirror end-to-end industry workflows.

3. *C-SMART Educational Framework*

3.1. *Framework Overview*

C-SMART (Construction Sustainability, Monitoring, and Automated Reality-capture Technique) is designed as an educational framework that integrates reality capture, AI-driven data processing, and immersive visualization into a coherent learning workflow for engineering students across civil and construction engineering, geomatics, and mechanical engineering students who are involved in the construction projects. Rather than focusing on individual tools or software platforms, the framework emphasizes end-to-end digital construction processes, enabling students to understand how spatial data are collected, analyzed, and used to support decision-making in modern construction environments.

The framework is structured around a modular pipeline that mirrors industry practice while remaining adaptable to academic settings. Students engage with sequential stages of the workflow, including reality-capture planning and data acquisition, automated point cloud processing, comparison of as-built and as-designed conditions, and interpretation of results through interactive visualization. This structure allows C-SMART to be implemented incrementally within existing courses, supporting both undergraduate and graduate instruction without requiring major curricular restructuring.

3.2. *Educational Design and Learning Objectives*

The educational design of C-SMART is guided by clearly defined learning objectives that extend beyond software proficiency to emphasize automation literacy and systems thinking. The framework aims to enable students to:

1. Understand the role of LiDAR-based reality capture in construction monitoring and quality control.
2. Apply AI and machine learning concepts for automated feature extraction and semantic interpretation of spatial data.
3. Interpret discrepancies between as-designed and as-built conditions within scan-to-BIM and digital-twin contexts.
4. Evaluate construction progress, safety considerations, and sustainability implications using data-driven evidence.
5. Collaborate across disciplines using shared digital models and visualization environments.

These objectives are addressed through project-based and laboratory activities in which students work with real or realistic construction datasets. Instructional modules are designed to emphasize process integration, encouraging students to reason about data flow, automation constraints, and decision impacts rather than isolated technical tasks. This approach supports the development of higher-level competencies aligned with industry expectations for digitally enabled construction professionals. (Table1).

Table 1. Mapping of C-SMART technologies to learning activities and educational outcomes

C-SMART Component	Student Learning Activity	Targeted Learning Outcomes
LiDAR reality capture (terrestrial, mobile, robotic)	Plan and collect spatial datasets; evaluate coverage and data quality	Spatial reasoning; data acquisition literacy
AI-based point cloud processing	Apply pre-processing (de-noising and geo-referencing), then automated segmentation and semantic classification workflows	Automation literacy; data-driven analysis
Scan-to-BIM comparison	Compare as-built and as-designed models to identify deviations and clashes	Systems thinking, quality control reasoning
Digital twin integration	Analyze progress and temporal changes in construction models	Construction process understanding
XR/MR visualization	Interpret spatial conditions through immersive interfaces	Spatial awareness; technical communication
Team-based project workflow	Collaborate using shared digital models and datasets	Interdisciplinary collaboration

3.3. *Technical Components Supporting Learning*

While C-SMART incorporates advanced technical components, these elements are introduced primarily as learning enablers rather than as standalone research contributions. Reality-capture activities involve terrestrial, mobile, or robotic LiDAR systems, allowing students to explore data acquisition strategies and understand trade-offs related to coverage, accuracy, and deployment constraints. Automated point cloud processing pipelines expose students to AI-based techniques for object recognition and semantic classification, reinforcing concepts related to data quality, model performance, and uncertainty.

Processed datasets are integrated into scan-to-BIM and digital-twin environments, where students compare as-built conditions against design models to identify deviations, sequencing issues, and potential safety or sustainability concerns. Immersive visualization using extended or mixed reality (XR/MR) is incorporated selectively to support spatial understanding and intuitive interpretation of complex 3D information. Importantly, the level of technical complexity is scaled to course objectives, ensuring that the framework remains feasible across different academic levels and institutional resources.

3.4. *Framework Feasibility and Scalability*

C-SMART is intentionally designed to be scalable and adaptable across institutions with varying levels of technical infrastructure. The modular structure allows instructors to implement individual components, such as point cloud analysis or visualization, independently, or to deploy the full workflow in advanced courses or capstone projects. Open-source or commonly available software tools can be used where appropriate, and datasets may be collected on-site or provided through curated repositories.

From an instructional perspective, the framework supports flexible integration into surveying, construction engineering, BIM, and digital construction courses. This adaptability enables programs to introduce automation concepts progressively while maintaining alignment with existing learning outcomes. The following section discusses the instructional context and applicability of the proposed framework and outlines considerations for future classroom deployment. (Figure1.)

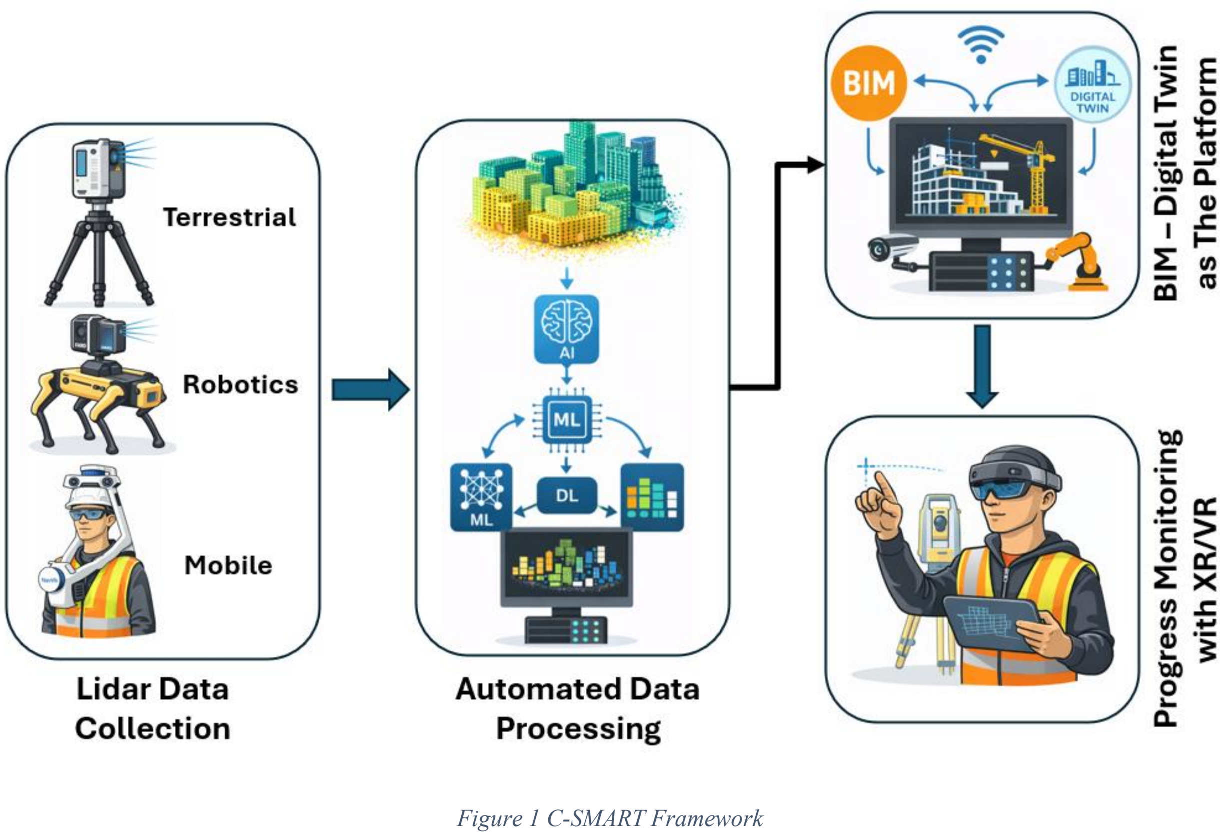

Figure 1 C-SMART Framework

4. *Educational Context and Framework Applicability*

4.1. *Course Context and Instructional Background*

The C-SMART framework is proposed as an integrated educational model informed by prior instructional and research experience with its individual components across undergraduate and graduate-level construction engineering and geomatics-related courses. These courses have included content related to surveying, digital construction, and construction monitoring, and have enrolled students from civil, construction, and geomatics engineering backgrounds. While the complete C-SMART workflow has not yet been deployed as a unified classroom implementation, its design reflects practices and learning activities that have been successfully incorporated into existing coursework.

The framework draws on laboratory exercises, project-based assignments, and team-oriented activities previously used to introduce reality capture, point cloud processing, and digital modeling concepts. These experiences informed the modular structure of C-SMART and its alignment with existing course objectives, ensuring that the proposed framework can be embedded within standard instructional schedules without requiring major curricular restructuring.

4.2. *Anticipated Instructional Modules and Learning Activities*

Within the proposed framework, students would engage with C-SMART through a sequence of instructional modules designed to reflect real-world digital construction workflows. Introductory activities would address reality-capture planning and LiDAR data characteristics, followed by automated point cloud processing using AI-based segmentation and classification techniques. Subsequent modules would focus on scan-to-BIM comparison and interpretation of as-built and as-designed discrepancies, with selected activities incorporating immersive visualization to support spatial understanding and communication. These modules are intentionally structured to emphasize workflow integration and interpretation rather than software-specific proficiency. Team-based activities are incorporated to support interdisciplinary collaboration and mirror professional construction environments. The framework is designed to prioritize feasibility and instructional value, enabling gradual adoption and adaptation across courses and institutions.

4.3. *Example Instructional Module Structure*

To provide greater clarity regarding classroom application, the C-SMART framework may be implemented as a structured semester-long sequence organized into progressive modules. Table 2 presents an example implementation model within a 14-week semester structure, illustrating module focus, student activities, and expected deliverables. The sequence is designed to scaffold student learning from data acquisition planning through automated analysis and professional communication, mirroring industry workflows while maintaining instructional feasibility.

Table 2. Example semester-long implementation of C-SMART instructional modules

Module	Timeline	Focus Area	Core Student Activities	Expected Deliverables
Module 1: Reality Capture Planning and Data Acquisition	Weeks 1–3	LiDAR workflow planning and data quality evaluation	Develop LiDAR acquisition plan; evaluate scanning positions; analyze occlusion risks; justify data collection strategy based on site constraints	Scan planning report; coverage evaluation diagram; data quality reflection
Module 2: AI-Based Point Cloud Processing	Weeks 4–6	Automated segmentation and classification	Perform registration and filtering; apply segmentation or classification workflows; evaluate model parameters and uncertainty	Technical memorandum documenting preprocessing steps, model performance metrics, and uncertainty analysis
Module 3: Scan-to-BIM Deviation and Progress Analysis	Weeks 7–10	As-built vs. as-designed comparison	Conduct deviation analysis; identify clashes or discrepancies; assess implications for schedule, quality control, and constructability	Annotated deviation report; impact assessment summary
Module 4: Visualization and Professional Communication	Weeks 11–14	Interpretation and engineering decision-making	Present findings using immersive or interactive visualization platforms; synthesize workflow results; connect analysis to engineering decisions	Professional technical report; visual presentation or XR-based demonstration

4.4. *Assessment Approach*

Student learning within the proposed C-SMART framework is intended to be evaluated using a combination of rubric-based project assessment, technical deliverables, and reflective components. Planned deliverables include processed point cloud datasets, annotated scan-to-BIM comparison results, and concise technical summaries documenting workflow decisions and interpretation of outcomes. Assessment criteria are designed to emphasize conceptual understanding, automation awareness, and systems-level reasoning in addition to technical correctness.

Reflective components are incorporated to capture student perspectives on the challenges and benefits of integrating reality capture, AI-based processing, and immersive visualization technologies. These reflections are intended to provide qualitative insight into student learning and engagement, complementing evaluation of technical outputs. The proposed assessment strategy is deliberately lightweight to ensure feasibility within standard course grading structures while still supporting meaningful evaluation of learning outcomes aligned with the framework's educational objectives. These assessment elements will be mapped to specific learning objectives to enable measurable evaluation of automation literacy, spatial reasoning, and system-level reasoning. (Table 3).

Table 3. Mapping of C-SMART learning objectives to assessment strategies.

Learning Objective	Performance Indicator	Assessment Method
Automation literacy	Ability to document AI-based workflow decisions	Rubric-based evaluation of technical report
Spatial reasoning	Accurate interpretation of scan-to-BIM deviations	Deviation analysis accuracy score
Systems thinking	Explanation of dependencies across data pipeline stages	Reflective analysis and workflow diagram
Interdisciplinary collaboration	Effective team coordination and communication	Peer evaluation and project rubric
Sustainability-informed reasoning	Identification of quality/safety/sustainability implications	Structured written interpretation

4.5. *Feasibility and Applicability*

The design of the C-SMART framework reflects instructional practices and technical workflows that have been previously applied in coursework and research settings in a modular and component-level manner. This prior experience informed the framework's emphasis on flexibility, allowing instructors to adopt selected components or implement the full workflow depending on course objectives, student background, and available resources. The modular structure supports application across surveying, construction engineering, BIM, and digital construction courses.

Potential implementation challenges include balancing technical depth with instructional time constraints and supporting students with diverse levels of prior exposure to digital tools. These considerations have been incorporated into the framework through scalable activity design and emphasis on interpretation rather than software mastery. Overall, the framework is intended to be adaptable to a range of institutional contexts and to support gradual adoption as programs expand their focus on automation and data-driven construction education.

5. *Anticipated Educational Outcomes and Observations*

5.1. *Anticipated Student Learning Outcomes*

Based on prior instructional and research experience with the individual components of the C-SMART framework, the integrated workflow is expected to support student engagement with digital construction processes beyond isolated technical tasks. Students are anticipated to develop competencies, evaluated using defined performance indicators aligned with the framework's learning objectives, including the ability to interpret LiDAR-derived point cloud data, apply automated processing techniques, and relate analytical outputs to construction progress and design intent. These outcomes align with the framework's emphasis on automation literacy and systems-level understanding of digital construction workflows.

The proposed framework is also expected to encourage students to recognize dependencies between data acquisition, processing, and visualization stages and to identify sources of uncertainty within automated pipelines. By engaging with end-to-end workflows, students would be positioned to develop a more holistic understanding of how reality-capture data support decision-making related to quality control, progress monitoring, and constructability assessment.

While these outcomes are currently anticipatory, future deployments of the C-SMART framework will incorporate structured assessment instruments to evaluate learning effectiveness. These will include rubric-based evaluation of technical deliverables, defined performance indicators aligned with learning objectives, and pre- and post-module assessment of automation literacy and spatial reasoning competencies.

5.2. *Anticipated Student Engagement and Learning Challenges*

Drawing on prior classroom experience with reality capture, point cloud processing, and digital modeling activities, the C-SMART framework is expected to promote high levels of student engagement through hands-on and interdisciplinary learning activities. Exposure to realistic datasets and integrated workflows is anticipated to enhance students' understanding of the practical relevance of AI, LiDAR, and visualization technologies beyond theoretical instruction. Immersive visualization components are expected to further support spatial understanding and communication within team-based learning environments.

At the same time, the framework acknowledges anticipated challenges related to dataset complexity and the learning curve associated with automated processing tools. These challenges highlight the importance of scaffolded instructional design and instructor guidance to support effective learning. Addressing such challenges is an intentional aspect of the framework, reinforcing critical interpretation rather than reliance on automated outputs.

5.3. *Instructional Insights Informing Framework Design*

The design of the C-SMART framework is informed by instructional observations from prior use of its individual components in coursework and research contexts. Modular activity structure and team-based workflows have been shown to support students with diverse academic backgrounds and facilitate peer learning. Emphasizing interpretation, reasoning, and communication over software execution has guided the development of assessment strategies aligned with the framework's educational objectives.

These instructional insights informed decisions related to activity scope, sequencing, and assessment emphasis within the proposed framework. By incorporating these lessons into the integrated design, C-SMART aims to provide a feasible and pedagogically grounded approach for introducing advanced digital construction concepts into engineering education.

5.4. *Limitations and Future Evaluation Needs*

As a conceptual framework, the outcomes discussed in this section represent anticipated educational benefits rather than measured results from a completed deployment. Formal classroom implementation and longitudinal assessment will be required to evaluate learning effectiveness quantitatively and across diverse student populations. Future work will focus on structured data collection and evaluation methods to validate and refine the framework's educational impact.

5.5. *Planned Pilot Implementation and Evaluation Strategy*

To address the need for empirical validation, pilot implementation of selected C-SMART modules is planned within an upper-level construction engineering course beginning in the upcoming academic cycle. The pilot will integrate LiDAR data acquisition, AI-based segmentation, and scan-to-BIM comparison activities into a semester-long project structured around a real or realistic construction dataset. Student learning will be evaluated using a mixed-methods assessment strategy, including pre- and post-module surveys to measure changes in automation literacy and spatial reasoning, rubric-based evaluation of technical deliverables, and reflective analysis of workflow interpretation and interdisciplinary collaboration. Quantitative measures will assess conceptual understanding and technical reasoning, while qualitative reflections will capture student perceptions of integrated digital construction workflows. Findings from this pilot deployment will inform iterative refinement of the framework and support future longitudinal assessment.

6. *Discussion*

6.1. *Educational Value and Workforce Readiness*

The C-SMART framework illustrates how advanced digital construction technologies can be structured within engineering education to emphasize systems thinking and automation literacy rather than isolated tool usage. By organizing reality capture, AI-based processing, and immersive visualization into an integrated workflow, the framework is designed to support student development of competencies related to spatial data interpretation, data-driven decision-making, and interdisciplinary collaboration. These competencies align with evolving workforce expectations as construction organizations increasingly rely on automated monitoring, digital twins, and AI-supported quality control processes.

By emphasizing interpretation and workflow integration, the framework is intended to encourage students to critically evaluate automated outputs and consider their implications for construction safety, quality, and sustainability. This educational focus reflects the reality of professional practice, where automation augments rather than replaces engineering judgment. As such, the framework is positioned to support workforce readiness by preparing students to operate effectively within complex, data-rich construction environments.

6.2. *Alignment with ABET Student Outcomes*

The C-SMART framework is purposefully designed to support student learning outcomes that align with ABET accreditation criteria for engineering programs. By integrating reality capture, AI-driven analysis, and interdisciplinary collaboration within authentic construction workflows, the framework reinforces competencies related to complex problem-solving, communication, and teamwork. Specifically, the ability to document AI-based workflow decisions and analyze scan-to-BIM deviation maps directly relates to the student's ability to identify and solve complex engineering problems while considering real-world constraints. Furthermore, the framework supports ACCE-related competencies in construction technology integration and project control through its emphasis on automated monitoring. By evaluating automation uncertainty and data limitations, students practice the ethical and professional responsibilities required in increasingly data-driven professional environments. This structured alignment ensures that the introduction of emerging technologies does not distract from, but rather enhances, the measurable achievement of core accreditation standards.

Table 4 Alignment of C-SMART activities with ABET student outcomes

C-SMART Activity	**Corresponding ABET Outcome**
AI-based workflow documentation	(1) Ability to identify, formulate, and solve complex engineering problems
Scan-to-BIM comparison and deviation analysis	(2) Ability to apply engineering design considering constraints
Team-based interdisciplinary project workflow	(5) Ability to function effectively on a team
Technical reports and workflow documentation	(3) Ability to communicate effectively
Evaluation of automation uncertainty and data limitations	(6) Ability to recognize ethical and professional responsibilities

Through this alignment, C-SMART provides a structured mechanism for embedding emerging digital construction competencies within accreditation-relevant learning frameworks.

6.3. *Scalability and Curriculum Integration*

A central design principle of the C-SMART framework is modularity, which supports adoption across courses with different objectives, levels, and resource constraints. Individual components may be introduced independently, or the full workflow may be implemented in advanced courses or capstone experiences. This flexibility enables integration across surveying, construction engineering, BIM, and digital construction curricula without requiring substantial restructuring.

To facilitate practical implementation, the C-SMART framework may be incorporated into engineering curricula through three progressive integration models:

1. **Embedded Module Model** – Individual C-SMART modules are integrated into existing courses such as Surveying, BIM, or Construction Methods, reinforcing automation literacy without introducing additional course requirements.
2. **Dedicated Digital Construction Course Model** – A standalone upper-level elective course structured around the full C-SMART workflow provides comprehensive exposure to automated monitoring, AI-based analysis, and digital twin concepts.
3. **Capstone Integration Model** – The framework is embedded within interdisciplinary capstone projects, where students apply reality capture and AI-driven analysis to real or simulated construction case studies, supporting systems-level learning and professional synthesis.

These integration pathways allow programs to adopt the framework incrementally while maintaining alignment with accreditation standards, faculty workload considerations, and institutional resource constraints.

From a curricular standpoint, the framework supports progressive integration, with foundational concepts introduced at lower levels and more advanced automation topics addressed in upper-level or graduate coursework. This staged approach enables programs to expand digital construction content incrementally while preserving alignment with existing learning outcomes. The framework's reliance on adaptable datasets and widely available software tools further enhances its applicability across institutions with varying technical infrastructure.

6.4. *Limitations and Future Research Directions*

As a conceptual educational framework, this work does not present empirical results from a fully integrated classroom deployment. The anticipated educational benefits discussed are informed by prior instructional and research experience with the framework's individual components rather than longitudinal assessment of the integrated system. Formal implementation and evaluation will be required to validate learning outcomes and assess effectiveness across diverse student populations and institutional contexts.

Future research will focus on deploying the integrated C-SMART framework in classroom settings and collecting structured assessment data to evaluate student learning over time. Planned extensions include deeper integration of XR and MR environments and investigation of how immersive visualization influences student comprehension, communication, and decision-making. These efforts will support continued refinement of the framework and contribute to broader understanding of how automation and digital technologies can be effectively integrated into construction engineering education.

6.5. *Technology Evolution and Framework Longevity*

While specific LiDAR platforms, AI libraries, or visualization tools will inevitably evolve, the C-SMART framework is intentionally designed to be technology-agnostic at the conceptual level. The pedagogical emphasis is placed on workflow integration, data reasoning, and automation literacy rather than proficiency in a specific software environment. As sensing hardware and AI tools advance, instructional modules can be updated or substituted without altering the underlying educational objectives or assessment structure. This modularity ensures that as programs expand their focus on automation, they can upgrade technologies while maintaining alignment with existing learning outcomes. Given the sustained industry shift toward digital twins, automated monitoring, and AI-supported quality control, the conceptual relevance of C-SMART is expected to remain applicable over the coming decade and beyond, even as specific products reach the end of their lifecycles. This approach reinforces the reality of professional practice, where automation is used to augment, not replace, engineering judgment.

7. *Conclusions and Future Work*

This paper presented C-SMART, an AI-driven educational framework designed to integrate LiDAR-based reality capture, automated point cloud processing, and immersive visualization into construction engineering education. By framing these technologies within an experiential and systems-based learning model, the framework addresses a gap between rapidly evolving industry practices and traditional educational approaches that often introduce digital tools in isolation. C-SMART is proposed as a modular and adaptable framework that supports integration of automation concepts into existing curricula while emphasizing interpretation, workflow integration, and engineering judgment rather than software proficiency alone.

The framework is intended to support the development of key competencies related to automation literacy, spatial reasoning, and interdisciplinary collaboration. By engaging students with end-to-end digital construction workflows, C-SMART is designed to promote a holistic understanding of how reality-capture data inform construction monitoring, quality control, and sustainability-related decision-making. Although this work does not present empirical results from a fully integrated classroom deployment, it provides a pedagogically grounded framework informed by prior instructional and research experience with its individual components.

Future work will focus on formal classroom implementation of the integrated C-SMART framework and the collection of structured assessment data to evaluate learning outcomes over time. Planned extensions include deeper integration of XR and MR environments to support immersive inspection and visualization tasks, as well as investigation of how such interfaces influence student comprehension, communication, and decision-making. Through continued refinement and evaluation, the C-SMART framework aims to contribute to scalable and educationally grounded approaches for preparing construction engineers to operate effectively in automated and data-driven professional environments.

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