

Impact of Digital Construction Technologies on Sustainability Awareness and Decision-Making in Civil Engineering Education

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Abstract: Digital technologies such as Building Information Modeling (BIM), Artificial Intelligence (AI), simulation platforms, and virtual and augmented reality are reshaping civil engineering education, yet their influence on sustainability awareness and decision-making is not well understood. This study surveyed 73 students enrolled in civil engineering courses at a public university in the southeastern United States. The instrument comprised 36 Likert-scale statements, grouped into eight constructs covering technology use in the curriculum, professional mindset, sustainability knowledge and lifecycle and environmental awareness. They also covered understanding of water resources, cognitive ability, emotional intelligence, and problem-solving. It also includes three decision scenarios in which a digital tool output conflicted with human input or practical constraints. Students reported favorable attitudes toward digital tools, along with strong conceptual sustainability awareness, but two applied-skill gaps stood out: only 32.9% felt able to interpret hydrologic models, and only 28.8% felt they could transfer simulation-based lessons to real world settings. In the scenarios, at most 12.3% of respondents accepted the digital output at face value, and 83.6% never did so across all three scenarios. Breadth of tool exposure was unrelated to perceptions or decision style, whereas the small group of students reporting exposure to hydrologic modeling rated their model interpretation ability substantially higher, suggesting that relevant depth matters more than the number of tools encountered. The findings support curricula that pair earlier and deeper BIM and hydrologic modeling instruction with lifecycle content and that train verification and interpretation skills alongside tool operation.

Keywords: Civil engineering education; sustainability awareness; digital construction technologies; decision-making; critical thinking.

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1. Introduction

Construction is currently undergoing tremendous change in its use of technology. This can be seen with the term "Construction 4.0" and refers to how many of the same technologies that are used in Industry 4.0, such as Industrial Internet of Things (IIoT), Big Data Analytics and cloud computing, are being incorporated into all aspects of the construction process (Statsenko et al., 2023). Many forms of AI have been utilized in the field of construction to assist with issues, including but not limited to Scheduling, Safety and even Optimization for other areas of construction. Despite many years of using new technologies in this area, construction remains one of the least digitally advanced fields (Abioye et al., 2021; Pan and Zhang, 2021). In addition to these advancements, Immersive Virtual Reality (IVR) has become increasingly popular in Construction Management Education. IVR is able to simulate real world construction environments and provide students with an immersive experience, allowing them to interactively learn about various aspects of the construction environment and processes (Ohueri et al., 2025).

These trends in practice will influence how civil engineers are educated. As such, universities around the world are now increasingly incorporating Geographic Information Systems (GIS), 3D / 4D modeling, AI-based tools, hydrological model software, simulating platforms and Building Information Modeling (BIM) into their undergraduate programs to prepare

graduates to meet current and future industry needs (Besné et al., 2021; Chacon, 2021). The built environment carries significant environmental burdens. Greenhouse gas emissions generated by buildings are substantial. Therefore, addressing this issue requires a focus on all stages of the building's life cycle rather than solely on operational energy (Röck et al., 2020). Digital tools are often touted as having the potential to enhance sustainability. For example, BIM has the potential to create lifecycle assessments in less time and at lower cost than traditional methods, and to reduce the time and cost barriers to environmental evaluations (Zimmerman et al., 2021). Consequently, there is good reason to believe that exposure to these digital construction technologies during civil engineering education may influence how students consider sustainability when making engineering decisions.

Although there is now much greater interest in teaching sustainable engineering principles, the field remains largely unexplored. There have recently been many reviews examining why the process of developing a curriculum is becoming increasingly complex as it relates to how to integrate sustainability, as well as how to assess the degree to which it is successfully integrated, (Nakad et al., 2024) research has shown that users can often rely too heavily on intelligent system (AI) suggestions and will accept them as correct even if they are incorrect (Buçinca et al., 2021); in addition, building appropriate levels of user trust within the AEC community has proven to be one of the most significant challenges related to the use of AI in the AEC industry (Emaminejad and Akhavian, 2022). Thus, whether civil engineering students trained with an increasing number of digital tools to support their training develop a balanced perspective on the application of those tools and link them to sustainability issues remains an unanswered question. As such, all available evidence currently falls into three relatively distinct bodies of literature: studies investigating the extent of student acceptance of digital construction tools, studies evaluating the effectiveness of integrating sustainability concepts into engineering curricula, and experimental work on individuals' reliance on outputs from intelligent systems. To date, few studies have investigated both areas concurrently in a common student population, nor do we know of any prior study that has used a combination of perceptions regarding sustainability and decision-making scenarios where digital tool outputs may contradict human judgments.

This study addresses that gap through a structured survey of students enrolled in civil engineering courses at a U.S. public university. The sample is dominated by sophomores and juniors (87.6% combined), so the findings describe students in the early-to-middle years of one program and should be read within that boundary rather than as claims about civil engineering students in general. Three Research Questions (RQs) guided the work. RQ1: What is the profile of student exposure to digital construction technologies in the sampled program? RQ2: How do students perceive digital tools in relation to their coursework, professional responsibility, sustainability, lifecycle knowledge, water resources understanding, and their own cognitive and problem-solving development? RQ3: How do students decide when a digital tool output conflicts with human judgment or practical constraints, and are those decisions related to their reported attitudes and exposure? The findings are intended to inform the integration of digital technologies into civil engineering curricula in ways that strengthen, rather than weaken, sustainability awareness and critical thinking. In addition to perception questions, this study uses scenario questions in which a digital tool's output conflicts with human input. The conflict stays the same across the three scenarios while its source changes, from a peer to an authority figure to the student's own manual work, so that stated attitudes can be compared with actual decisions in each situation. This study is descriptive and exploratory. It examines students' experience, perceptions, and decision responses, and looks for possible relationships among them. It does not test cause-and-effect relationships.

2. Literature Review

2.1. Digital Technologies and Their Acceptance in Civil Engineering Education

BIM education has received the most sustained research attention among digital construction technologies. A systematic review of BIM implementation in the academic field, covering higher education institutions worldwide, found that integration strategies vary widely, that no common set of regulatory guidelines exists to anchor them, and that the connection between institutional education and professional practice remains weak (Besné et al., 2021). Complementing such reviews, course-level work has begun to design Construction 4.0 learning activities directly: Chacón (2021) reported a program of STEAM-oriented cornerstone, capstone, and workshop activities built to infuse Construction 4.0 technologies into a civil engineering degree using open and affordable hardware and software. A decade-spanning review of immersive VR in construction management education synthesized advances in the technology from 2014 to 2024 and flagged open issues for educators, including how to assess the soft skills students acquire in immersive environments (Ohueri et al., 2025).

A second body of work asks how students receive these technologies. Technology acceptance research, anchored in models that link perceived usefulness and ease of use to adoption intentions, has been applied extensively to educational technology, supporting a systematic review (Granić and Marangunić, 2019). In the AEC domain specifically, an analysis of 773 student survey responses at an Australian university found that perceived usefulness and general attitude dominated student commentary on BIM, that attitudes were largely positive, and that enthusiasm coexisted with concerns about the learning curve and about the consequences of coupling BIM with AI; civil engineering students in that sample tended to frame BIM through design validation rather than project delivery (Ahankoo et al., 2025). Student perceptions of BIM adoption have also been examined in national contexts where BIM use is not mandated (Goel, 2025). These acceptance studies establish that student attitudes toward digital construction tools are broadly favorable across institutional contexts. However, they stop short of examining what students do with tool outputs or whether exposure to tools relates to sustainability thinking. In particular, they measure attitudinal endorsement rather than applied capability, a distinction the competencies literature in section 2.2 makes central; the present study measures both. So, Hydrologic modeling instruction has received less attention than BIM or VR in the literature reviewed above. Instructors in this area report difficulty finding high-quality materials that engage students in complex real-world problems, and the enhancements the field calls for include exposure to data and modeling tools, active learning, and real-world case studies (as summarized by Byrd et al., 2022).

Evaluating fifteen online modules built around authentic, high-cognitive-demand tasks, used by 299 students at fifteen U.S. universities, Byrd et al. (2022) found that students reported meaningful gains in conceptual understanding and technical skills, indicating that well-designed digital instruction can support applied modeling competence. Coverage of AI in civil engineering education is likewise only now emerging.

2.2. Sustainability Competencies and Lifecycle Thinking in Engineering Curricula

Interest in embedding sustainability in engineering programs has grown steadily over the past two decades, yet a PRISMA-based review of 30 studies found fourteen different methods used to assess that integration, each with limitations, and recommended combining at least two methods to evaluate curricula reliably (Nakad et al., 2024). Part of the difficulty lies in what should be assessed. The key competencies literature in sustainability education describes the intended outcomes not as bodies of factual knowledge but as interlinked clusters of knowledge, skills, and attitudes. A Delphi study with international experts largely confirmed the most widely cited competency framework, extended it and positioned it as a reference for program design and evaluation (Brundiars et al., 2021). Since these competencies combine knowledge, skills, and attitudes, measuring any one of them alone yields an incomplete picture, yet few of the empirical studies of students reviewed here capture all three simultaneously. Subsequent synthesis work documents broad agreement across frameworks on the core competency set (Redman and Wiek, 2021). A recurring theme in this literature is the gap between awareness of sustainability problems and the ability to act on them, suggesting that surveys of engineering students should separate declarative awareness from self-assessed applied capability.

In the built environment domain, the case for lifecycle thinking has sharpened: a systematic analysis of more than 650 building Lifecycle Assessment (LCA) cases showed that as operational energy performance improves, embodied greenhouse gas emissions come to dominate the life cycle, making whole-lifecycle evaluation essential for climate mitigation (Röck et al., 2020). Digital tools are increasingly connected to this agenda: an investigation of industry practice found that linking BIM data to LCA offers significant efficiency potential for environmental assessment, although workflows are still in their early stages of development and face data and integration challenges (Zimmermann et al., 2021). At the student level, however, teaching experience with LCA and digital tools remains limited. A long-term account of teaching LCA to undergraduates through a learning-by-doing design studio found that students can apply LCA in their own design work when equipped with adequate software tools, while noting that most published LCA teaching experience involves engineering students at the graduate level (Gomes et al., 2022). Taken together, these studies suggest that digital tools and sustainability education can reinforce each other, but they say little about whether students actually develop that connection.

2.3. Technology Reliance and Engineering Decision-Making

Research on human interaction with intelligent systems offers a useful lens for understanding how students may respond to digital tool outputs. Experimental work on AI-assisted decision-making shows that people frequently over-rely on AI recommendations, accepting suggestions even when they are wrong, and that interventions that force more deliberate thinking can reduce this over-reliance (Bućinca et al., 2021). Later work reframed the problem: rather than treating overreliance as an unavoidable cognitive bias, it modeled engagement with an AI output as a strategic choice in which people weigh the cost of verifying against the cost of simply relying, and showed that explanations reduce overreliance when they sufficiently lower the cost of verification (Vasconcelos et al., 2023). This cost-benefit framing generates an expectation for classroom scenarios: when a low-effort alternative to verification is available, for example, deferring to an authority figure, many decision-makers should take it, and independent verification should be most common when no such shortcut exists. This reasoning directly shaped the present study: the three scenarios were built to vary the cost of the alternative to verification by changing the source of the conflicting human input, as described in the 3.1 Survey Instrument and Construct Rationale section.

Specifically, to the AEC domain, a systematic review of two decades of research on the subject found that user acceptance of artificial intelligence and robotics is dependent upon the users' trusting the technology; however, the researchers also concluded that explainability and establishing "calibrated" levels of trust will be critical areas of focus for the AEC industry (Emaminejad and Akhavan, 2022). The advent of Generative AI further expands the scope of this issue. Text-based models are being incorporated into construction workflows at an exponential rate, outpacing the development of guidelines for their proper use. Similarly, Ghimire et al. (2024) note that Generative AI is currently under examination in Engineering Education as a disruptor to traditional teaching methods and possibly as a means of incorporating sustainable practices into existing heavy technical curricula (Cañavate et al., 2025). To date, empirical evidence regarding student use and perception of Generative AI has begun to emerge. Uddin et al. conducted a study involving 44 civil engineering students who utilized ChatGPT as a support resource. The results of this study showed that students wrote more comprehensive and detailed answers using the tool and were generally positive about it (Uddin et al., 2024). Studies such as this one can help measure student behavior related to usage and acceptance; however, to the authors' knowledge, no prior studies have investigated students' behavior regarding whether they verify or accept tool output when conflicting information exists. Findings like these matter for education, as students may develop habitual patterns of verifying or accepting the output of tools (i.e., VR safety simulators, AI scheduling software, BIM-based quantity take-off) before ever leaving the classroom.

2.4. Theoretical Framework and Research Gap

The study draws on three ideas from the literature above as its framework. First, technology acceptance research links perceived usefulness and general attitude to students' adoption of digital tools in their studies (Granić and Marangunić, 2019; Ahankoob et al., 2025). This idea frames the two constructs on technology use in the curriculum and professional mindset. Second, the key competencies perspective in sustainability education separates knowing about sustainability from being able to act on that knowledge (Brundiars et al., 2021; Redman and Wiek, 2021). This idea frames the sustainability, lifecycle, and

water resources constructs, with attitude items kept separate from capability items. Third, the cost-benefit account of reliance on intelligent systems treats engagement with a tool's output as a choice that depends on whether verifying seems worth the effort relative to simply relying on it (Bućinca et al., 2021; Vasconcelos et al., 2023). This idea frames the three decision scenarios and yields one expectation: verification should be most common when no low-effort alternative exists, and deference should rise when one is available.

All three concepts support the research questions through very straightforward means. The acceptance concept supports RQ2, the competence concept supports RQ2 and allows researchers to identify gaps in skills development, and the reliance concept supports RQ3. RQ1 establishes the exposure context for each of the three. Based upon this, the three research Gaps represent three distinct areas. First, studies that collect data on digital tool exposure, sustainability perceptions, and decision-making using a common sample population are limited. Studies typically focus on measuring attitudes toward digital tools, studying how to integrate sustainability into curricula, and conducting reliability studies outside of Engineering Education. Second, nearly all studies of students examine only attitudes and do not include data on how students respond to conflicting information in a tool's output in real-world situations. Third, current research often does not distinguish between the number of different tools a student has been exposed to (i.e., Breadth) and the development of sustained learning with a single tool (i.e., Depth). Therefore, the evidence needed to compare students' breadth and depth levels has not been collected. Therefore, this study addresses all three gaps, which motivate the research questions.

3. Research Method

3.1. Survey Instrument and Construct Rationale

A structured fifteen question survey was built and administered through Microsoft Forms. It opened by stating the study's purpose and recording informed consent, then captured major and academic level, and used one multiple-selection item to record exposure to nine categories of digital tools: GIS/remote sensing, structural analysis, hydraulic/hydrologic modeling, AI-based tools, VR/Augmented Reality (AR), simulation tools, BIM, 3D/4D modeling, and scheduling and visualization software. Its core was 36 statements rated on a five-point Likert scale from Strongly Disagree (1) to Strongly Agree (5), grouped into eight constructs (Table 1).

The constructs were derived from themes identified in the literature rather than from a single validated scale. The technology use and professional mindset items reflect the acceptance and reliance literature, covering both the perceived value of digital tools in coursework and the concerns about responsibility, accuracy, and overreliance raised by studies of AI-assisted decision-making (Bućinca et al., 2021; Emaminejad and Akhavian, 2022). The sustainability knowledge, LCA and environmental awareness, and water resources constructs operationalize the distinction, emphasized by the competency literature, between declarative awareness and self-assessed applied capability (Brundiers et al., 2021): each of these blocks contains both attitude items (for example, that impacts should be considered early) and capability items (for example, that the respondent can interpret hydrologic models). The cognitive ability, emotional intelligence, and problem-solving constructs were included to capture how students see digital tools affecting their own thinking, engagement, and preparation. Several constructs deliberately mix favorable and cautionary statements about technology, for example, pairing "simulations give realistic practice" with "hands-on work is superior to simulations". This choice reduces the risk that agreement bias inflates a uniformly positive picture, at a known cost to internal consistency, and it shapes the analysis strategy described below. Before administration, the draft instrument was thoroughly reviewed by two faculty research team members with expertise in construction engineering and management to validate its content. The item wording was refined based on the review and feedback.

The final three questions posed decision scenarios pitting a digital tool's output against human input or practical constraints: a VR safety simulation showing no hazards while a teammate recalls one from site photos (scenario 1), an AI scheduler proposing a shorter sequence against an instructor's rework warning (scenario 2), and a cost-estimating task in which the student's own BIM quantity takeoff gives lower quantities than the student's own manual estimate, with no external human input (scenario 3). For each, respondents chose to accept the digital output, rely on the human input, or verify independently. Following the cost-benefit reasoning in section 2.3, the three scenarios hold the basic conflict structure constant while varying the source of the competing human input, and with it the cost of the alternative to verification. , from a peer (scenario 1) to an authority figure (scenario 2) to the respondent's own manual work (scenario 3). This design allows general caution toward digital outputs to be separated, at least partially, from deference to authority. Also, as the survey was distributed through civil engineering courses and student groups, the number of students reached, and therefore the response rate, cannot be established.

3.2. Data Collection and Sample

Participation was voluntary, and responses were anonymous; no names, email addresses, or other identifying information were recorded. The survey was distributed to students enrolled in civil engineering courses in the civil and environmental engineering school of a public university in the southeastern United States [institution name withheld for double-blind review], and 73 complete responses were received, with an average completion time of 4 minutes and 7 seconds. It is possible that some students responded quickly without full attention, which is acknowledged as a limitation in response quality in section 5.4. The respondents were predominantly civil engineering undergraduates; the sample also included a small number of environmental engineering and other-major students, as well as one graduate student, as detailed in Table 2. The de-identified dataset and the scripted analysis pipeline that reproduces every statistic, table, and figure in this paper are available from the corresponding author on reasonable request.

3.3. Data Screening and Quality Checks

The exported dataset contained 73 records and 43 fields. Screening found no duplicate respondent identifiers, no duplicate records, and no missing responses on any of the 36 Likert items or the three scenario items, so all 73 responses were retained without imputation or exclusion. Response labels were checked against the intended five-point scale; the only inconsistency was a lowercase variant of one anchor label (“Strongly disagree”) produced by the survey platform, which was normalized by case-insensitive matching before numeric coding. The raw export was preserved unchanged, and all cleaning steps are implemented in the scripted analysis pipeline. A response-consistency check identified two respondents (2.7%) who selected neutral on all 36 items. They were kept since all-neutral is a reasonable response to mixed-wording items, and removing them shifts agreement percentages by at most 3 points and changes no conclusions.

3.4. Analytical Approach

Likert responses were coded from 1 (strongly disagree) to 5 (strongly agree). For each item, we calculated the mean, Standard Deviation (SD), and percentage selecting “agree” or “strongly agree” (“% agree”), with Wilson score 95% Confidence Intervals (CI), which perform better than standard normal-approximation intervals for small samples (Brown et al., 2001). Cronbach’s alpha was used to assess item-group consistency (Table 1). Technology use in the curriculum and understanding of water resources each had $\alpha = 0.80$, while general sustainability knowledge had $\alpha = 0.71$. The other groups had lower values, mainly because they mixed positive and cautionary views of technology, so they were analyzed item by item, and no combined score was used in the main analysis. Group means in Table 1 are descriptive only. Exploratory factor analysis was not conducted because the sample ($n = 73$) is too small for a 36-item pool. The eight groups were derived from a literature synthesis and have not been empirically validated, as noted in section 5.4.

Exploratory analyses included Mann-Whitney U tests comparing sophomores ($n = 32$) and juniors ($n = 32$) on the eight construct means, with rank-biserial correlations as effect sizes. Spearman correlations examined whether breadth of digital tool exposure, measured as the number of tool categories selected, was related to construct means, the two weakest capability items, and scenario behavior. This measure treats all tool categories equally and does not capture duration or depth of use; tool-specific comparisons provide one view of depth, while measures such as hours of use or courses completed are left for future work. Students reporting hydrologic modeling exposure were compared with others on the hydrologic interpretation item, and students reporting BIM exposure were compared on the BIM waste item. These subgroups were small ($n = 8$ and $n = 6$), so results are descriptive and test statistics are reported for reference only. Spearman correlations were also examined to assess associations between four professional mindset items and two behavioral counts: scenarios in which respondents accepted the digital output and scenarios in which they chose to verify it. Agreement in verified choices across scenario pairs was tested using Fisher’s exact test and the phi coefficient. All analyses were exploratory. P-values are uncorrected, eight or more related tests are included in each family, and no single uncorrected result is treated as confirmatory. Nonparametric methods were used because responses are ordinal and the composite scores are short averages of ordinal items. Analyses were performed in Python using pandas and SciPy.

Table 1. Structure of the survey instrument, internal consistency, and construct-level descriptive statistics

Construct	Items	Example item	Cronbach’s α	Mean (SD)
Technology use in curriculum	4	Digital tools make coursework more engaging	0.80	3.96 (0.62)
Professional mindset	5	I am personally responsible, even with digital tools	0.49	3.76 (0.47)
General sustainability knowledge	4	I understand impacts of construction pollution	0.71	3.98 (0.48)
LCA and environmental awareness	5	Lifecycle impacts influence decisions	0.61	4.00 (0.40)
Water resources understanding	5	I can interpret hydrologic models	0.80	3.75 (0.63)
Cognitive ability	4	Tools don’t replace thinking	0.51	3.77 (0.51)
Emotional intelligence	5	Real tasks + simulations help	0.59	3.80 (0.49)
Problem-solving	4	Hands-on > simulations	0.37	3.80 (0.49)

Note: construct means are unweighted averages of item responses (1 = Strongly Disagree to 5 = Strongly Agree) and are reported for descriptive purposes only; constructs with α below 0.70 are interpreted at the item level.

4. Results

4.1. Respondent Profile and Exposure to Digital Tools

Table 2 summarizes the sample. Nearly all respondents (94.5%) were civil engineering majors, and the sample was dominated by sophomores and juniors, who each accounted for 43.8% of responses. Fig. 1 shows exposure to digital tools. GIS/remote sensing and 3D/4D modeling were the most common (47.9% each), followed by AI-based tools (43.8%). Exposure to BIM (8.2%), structural analysis tools (8.2%), and hydraulic/hydrologic modeling (11.0%) was low, consistent

with the sample's sophomore-junior concentration, since these tools typically appear in upper-level courses. On average, respondents reported experience with 2.3 tool categories (median 2, range 1 to 9).

Table 2. Respondent profile (n = 73)

Item	Mean	SD	Agree (%)	95% CI
Technology use in curriculum				
I prefer courses that integrate digital tools early	3.85	0.74	69.9	[58.6, 79.2]
Students should be introduced earlier to advanced tools	4.04	0.79	82.2	[71.9, 89.3]
Digital tools make coursework more engaging	4.00	0.69	76.7	[65.8, 84.9]
Digital tools improve understanding	3.95	0.91	74.0	[62.9, 82.7]
Professional mindset				
Digital tools are more accurate than humans	3.45	0.93	43.8	[33.0, 55.2]
I am personally responsible even with digital tools	4.10	0.73	86.3	[76.6, 92.4]
AR/VR can't replace physical presence	4.07	0.89	76.7	[65.8, 84.9]
Presence of digital tools generates overreliance	3.51	0.84	49.3	[38.2, 60.5]
I am ready to defend my digital-driven decisions	3.66	0.69	58.9	[47.4, 69.5]

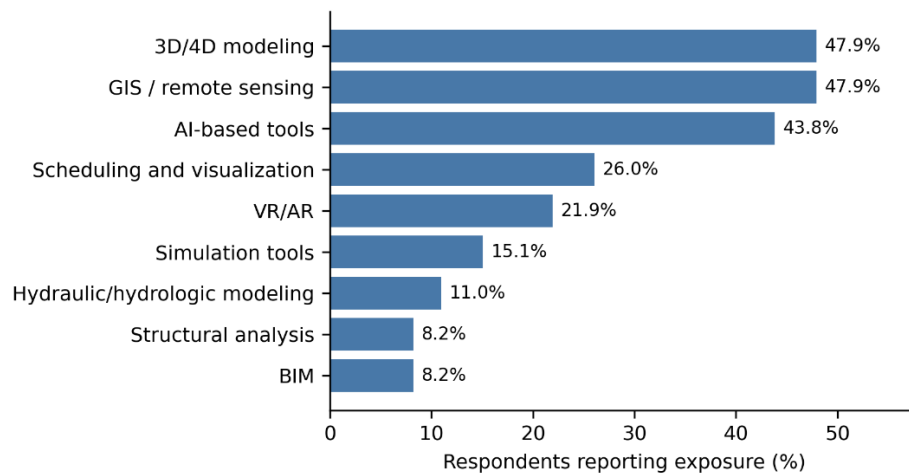


Fig. 1. Reported exposure to digital tool categories (n = 73)

4.2. Attitudes Toward Technology in Coursework and Professional Mindset

Table 3 reports the items on technology use in the curriculum and professional mindset, with 95% confidence intervals for the agreement percentages. Students were clearly favorable toward digital tools in coursework: 82.2% agreed that students should be introduced to advanced tools earlier, 76.7% found that digital tools make coursework more engaging, and 74.0% agreed that digital tools improve understanding. At the same time, the professional mindset items show that this enthusiasm is not uncritical. Only 43.8% agreed that digital tools are more accurate than humans, with an equal share remaining neutral. A strong majority (86.3%, 95% CI 76.6 to 92.4) agreed that they remain personally responsible even when using digital tools, and 76.7% agreed that AR/VR cannot replace physical presence. Concern about overreliance was present but not dominant: 49.3% agreed that the presence of digital tools generates overreliance, while 42.5% were neutral. Only 58.9% felt ready to defend decisions driven by digital tools, suggesting that confidence in justifying tool-based decisions lags behind willingness to use the tools.

4.3. Sustainability Awareness, Lifecycle Thinking, and Water Resources

Table 4 presents the sustainability-related items, while Fig. 2 shows the full response distributions for selected high- and low-agreement items. Sustainability awareness was generally strong: 90.4% of students agreed that they consider environmental impacts, 84.9% understood the impacts of construction pollution, and 84.9% understood lifecycle analysis. Attitudes were similarly positive, with 90.4% agreeing that impacts should be considered early in a project and 87.7% that lifecycle impacts influence their decisions. In addition, 89.0% agreed that digital tools help evaluate environmental impacts. The main exception was BIM, where only 45.2% agreed that it improves understanding of waste, and 54.8% were neutral, consistent with the very low BIM exposure (8.2%) in the sample. The water resources items showed a clearer gap. Although

86.3% agreed that models help identify drainage issues and 83.6% that environmental modeling aids decisions, only 32.9% (95% CI 23.2 to 44.3) agreed that they can interpret hydrologic models, while 45.2% disagreed (mean 2.93, the only item mean below 3.0 in the survey). Understanding of stormwater effects was also moderate at 58.9% agreement. Overall, students value hydrologic and environmental modeling but do not yet feel confident using the outputs, which is consistent with the low reported exposure to hydraulic/hydrologic modeling tools (11.0%).

Table 3. Technology use in curriculum and professional mindset items (n = 73)

Item	Mean	SD	Agree (%)	95% CI
Technology use in curriculum				
I prefer courses that integrate digital tools early	3.85	0.74	69.9	[58.6, 79.2]
Students should be introduced earlier to advanced tools	4.04	0.79	82.2	[71.9, 89.3]
Digital tools make coursework more engaging	4.00	0.69	76.7	[65.8, 84.9]
Digital tools improve understanding	3.95	0.91	74.0	[62.9, 82.7]
Professional mindset				
Digital tools are more accurate than humans	3.45	0.93	43.8	[33.0, 55.2]
I am personally responsible, even with digital tools	4.10	0.73	86.3	[76.6, 92.4]
AR/VR can't replace physical presence	4.07	0.89	76.7	[65.8, 84.9]
Presence of digital tools generates overreliance	3.51	0.84	49.3	[38.2, 60.5]
I am ready to defend my digital-driven decisions	3.66	0.69	58.9	[47.4, 69.5]

Table 4. Sustainability knowledge, LCA and environmental awareness, and water resource items (n = 73)

Item	Mean	SD	Agree (%)	95% CI
General sustainability knowledge				
I understand impacts of construction pollution	4.01	0.70	84.9	[75.0, 91.4]
I consider environmental impacts	4.14	0.61	90.4	[81.5, 95.3]
I know sustainable materials	3.78	0.67	72.6	[61.4, 81.5]
I understand lifecycle analysis	3.99	0.63	84.9	[75.0, 91.4]
LCA and environmental awareness				
Digital tools help evaluate impacts	4.07	0.54	89.0	[79.8, 94.3]
BIM improves waste understanding	3.51	0.60	45.2	[34.3, 56.6]
I identify sustainability trade-offs	3.64	0.63	61.6	[50.2, 71.9]
Impacts should be considered early	4.48	0.71	90.4	[81.5, 95.3]
Lifecycle impacts influence decisions	4.29	0.68	87.7	[78.2, 93.4]
Water resources understanding				
I understand stormwater effects	3.56	0.93	58.9	[47.4, 69.5]
Models help identify drainage issues	4.11	0.66	86.3	[76.6, 92.4]
I can interpret hydrologic models	2.93	1.13	32.9	[23.2, 44.3]
Stormwater should influence decisions	4.03	0.73	78.1	[67.3, 86.0]
Environmental modeling aids decisions	4.10	0.69	83.6	[73.4, 90.3]

4.4. Cognitive Ability, Emotional Intelligence, and Problem-Solving

Table 5 reports the remaining constructs; several of these items also appear in the response distributions shown in Fig. 2. The strongest single result in the survey is that 91.8% of students (95% CI: 83.2 to 96.2) agreed that tools do not replace thinking (mean: 4.40). Opinions on the constraining side of technology were more divided: about half agreed that digital workflows may limit creativity (50.7%) and that they apply engineering manually (50.7%), and 61.6% felt they could adapt without digital guidance. On the emotional intelligence items, students strongly endorsed combining real tasks with

simulations (93.2% agreement), yet only 35.6% said they prefer technology-based solutions; a majority (57.5%) were neutral, and 74.0% acknowledged that heavy reliance on technology affects awareness.

The problem-solving items sharpen this picture. Students clearly value physical experience: 86.3% agreed that hands-on work is superior to simulations, and 86.3% agreed that they would feel less prepared without real-world work. Confidence in simulations as realistic practice was moderate (54.8%), and the weakest applied-skill item in this group was the transfer of digital lessons to real settings, which only 28.8% of students endorsed (95% CI 19.7 to 40.0) while 56.2% remained neutral. Combined with the hydrologic model interpretation result above, the data indicate that the main deficit is not attitude but the ability to carry digital learning into practice.

As an exploratory screen, Mann-Whitney U tests comparing sophomores ($n = 32$) and juniors ($n = 32$) on the eight construct means found no consistent differences by academic level. Only the emotional intelligence construct reached nominal significance (sophomore mean 3.91 versus junior mean 3.66, $U = 659.5$, $p = 0.046$, rank-biserial $r = 0.29$), and this result does not survive correction for the eight comparisons performed; the remaining seven effect sizes were small (absolute rank-biserial are between 0.05 and 0.12). The perceptions reported here, therefore, appear to be broadly shared across the sophomore and junior groups.

Table 5. Cognitive ability, emotional intelligence, and problem-solving items ($n = 73$)

Item	Mean	SD	Agree (%)	95% CI
Cognitive ability				
Tools don't replace thinking	4.40	0.68	91.8	[83.2, 96.2]
Workflows may limit creativity	3.51	0.90	50.7	[39.5, 61.8]
I adapt without digital guidance	3.66	0.85	61.6	[50.2, 71.9]
I apply engineering manually	3.52	0.75	50.7	[39.5, 61.8]
Emotional intelligence				
Technology influences teamwork	3.63	0.96	60.3	[48.8, 70.7]
Real tasks + simulations help	4.30	0.59	93.2	[84.9, 97.0]
I engage with tech tasks	3.77	0.75	65.8	[54.3, 75.6]
I prefer tech-based solutions	3.36	0.77	35.6	[25.6, 47.1]
Heavy reliance affects awareness	3.96	0.84	74.0	[62.9, 82.7]
Problem-solving				
Hands-on > simulations	4.29	0.74	86.3	[76.6, 92.4]
Simulations give realistic practice	3.42	0.94	54.8	[43.4, 65.7]
I transfer digital lessons	3.18	0.84	28.8	[19.7, 40.0]
Without real-world work, I feel less prepared	4.32	0.78	86.3	[76.6, 92.4]

4.5. Scenario-Based Decision-Making

Fig. 4 summarizes the three decision scenarios. In scenario 1 (VR safety check), 68.5% of students chose to verify the potential hazard independently, 27.4% trusted the teammate's recollection, and only 4.1% trusted the VR output despite the deadline pressure. In scenario 2 (AI scheduling under time pressure), 74.0% followed the instructor's warning, 21.9% chose to verify, and only 4.1% accepted the AI plan. In scenario 3 (BIM versus manual estimate), 47.9% chose to verify, 39.7% trusted the manual estimate despite its warning about missed details, and 12.3% accepted the BIM output. Across all three scenarios, no more than 12.3% accepted the digital result without checking it first, which is consistent with the survey finding that students generally felt responsible for their own decisions and did not view digital tools as more reliable than people. The responses also depended on who provided the information: students mostly verified when it came from a peer in scenario 1, but relied more on the instructor's judgment in scenario 2. Scenario 3 was the most divided, with responses nearly split between verification and trust in the manual estimate. Overall, students generally preferred to verify results and tended to place more trust in human judgment than in automated outputs.

Individual-level results reinforce the overall pattern. Most respondents (61 of 73, or 83.6%; 95% CI, 73.4 to 90.3%) did not accept the digital output in any scenario. Nine students (12.3%) accepted it once, 3 (4.1%) accepted it in two scenarios, and none accepted it in all three. Independent verification was chosen at least once by 76.7% of respondents, in two or more scenarios by 45.2%, and in all three by 16.4%. Verification was also moderately consistent across scenarios, with pairwise phi coefficients of 0.29 to 0.35 and Fisher's exact p-values from 0.004 to 0.015 across the three scenario pairs. This suggests that the cautious decision style was not driven by a small subgroup but was a moderately stable tendency across the sample.

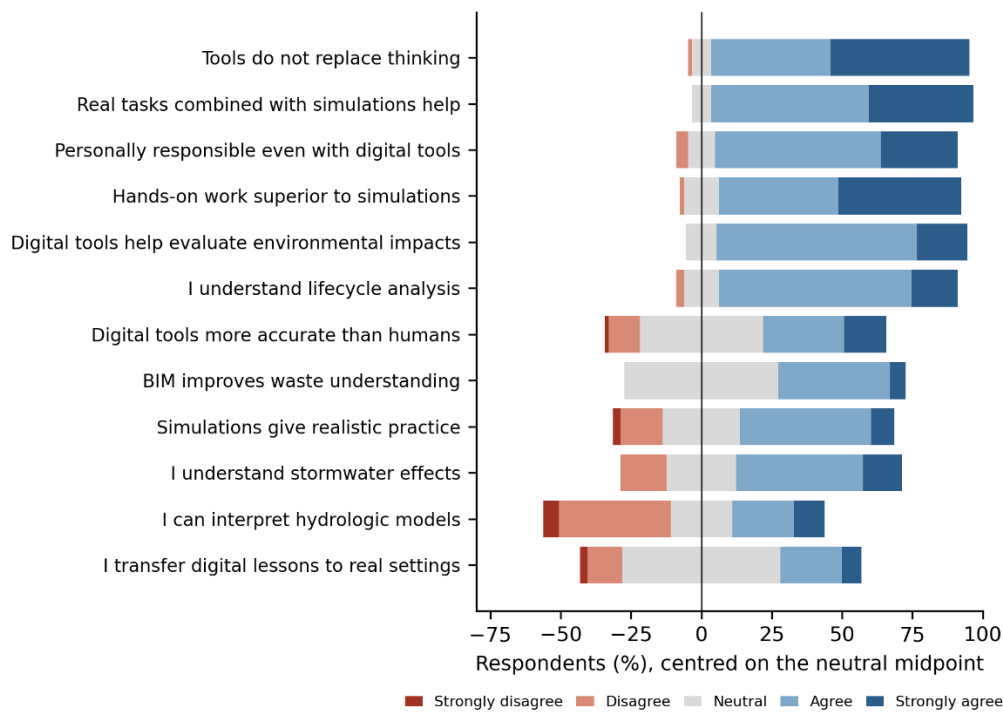


Fig. 3. Response distributions for twelve selected items (n = 73)

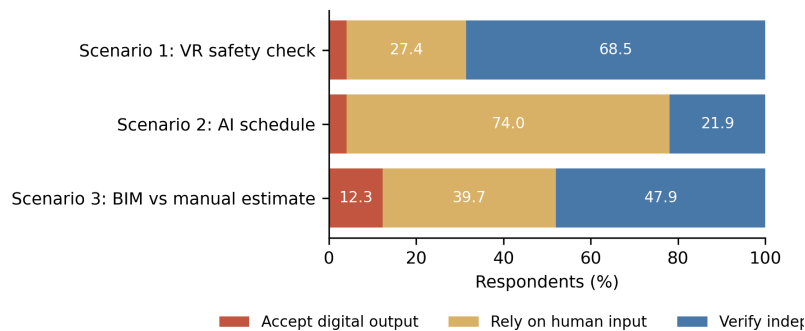


Fig. 4. Responses to the three decision scenarios (n = 73)

4.6. Exposure, Attitudes, and Decision Behavior

Spearman correlations showed no meaningful relationship between breadth of digital tool exposure and the eight construct means ($\rho = -0.18$ to $+0.06$, all $p > 0.13$). Breadth was also unrelated to hydrologic model interpretation ($\rho = +0.04$), transfer of digital lessons ($\rho = 0.00$), or the number of scenarios in which students chose to verify ($\rho = -0.03$, $p = 0.785$), suggesting that exposure to more tool categories did not correspond to stronger applied skills, sustainability awareness, or different scenario behavior. Specific tools exposure had different patterns. It should be noted that subgroups were small. The eight students exposed to hydraulic/hydrologic modeling rated their ability to interpret hydrologic models higher than the remaining 65 (mean 3.88, SD 0.83, versus 2.82, SD 1.12; Mann-Whitney $U = 400$, $p = 0.010$, rank-biserial $r = 0.54$) and also reported higher understanding of stormwater effects (4.00 versus 3.51). Because only eight students were exposed and exposure was self-selected, this finding is descriptive and may partly reflect more capable students choosing hydrology coursework, but it fits a relevant-depth explanation and contrasts with the null result for breadth. The BIM comparison was less informative: the six BIM-exposed students did not rate the BIM waste item appreciably higher than the others (3.67 versus 3.49, $p = 0.379$), and the comparison had very little power. So, both subgroup comparisons are considered descriptive. The test statistics are reported for reference only. Attitudes and scenario behavior were also only loosely related. Of eight exploratory correlations between four professional mindset items and two behavioral counts, the only nominally significant result was that students who viewed digital tools as more accurate than humans accepted digital outputs in more scenarios ($\rho = 0.27$, $p = 0.019$), but this did not survive correction for eight tests (Bonferroni threshold 0.006). There was a low-level, non-statistically significant positive relationship between personal responsibility and verification ($\rho = 0.21$, $p = .074$); willingness to defend your digitally based decision did not relate to acceptance ($\rho = 0.15$, $p = .212$) overall. The group-level agreement between stated and observed caution was consistent, which is reassuring for the attitude items. However, no single attitude item reliably identified the small minority who accepted digital outputs, making attitude questions alone an unreliable way to screen for overreliance risk in this population.

Cross-analyses among key items, all exploratory with uncorrected p-values, show the same loose coupling. Students who agreed that digital tools are more accurate than humans did not rate their hydrologic interpretation ability higher (mean 2.78, $n = 32$, versus 3.05, $n = 41$; $\rho = -0.19$, $p = 0.101$), belief in hands-on work showed only a weak, non-significant association with the transfer item ($\rho = 0.21$, $p = 0.075$), and self-rated hydrologic capability was unrelated to the number of scenarios verified ($\rho = -0.11$, $p = 0.352$). General optimism about tools does not appear to stand in for capability with a specific tool.

5. Discussion

5.1. Enthusiasm without Complacency

The first pattern is enthusiasm without complacency. Students find digital tools engaging and want their early introduction. Again, they still believe that tools do not replace thinking or the user's responsibility; AR/VR cannot replace physical presence. The participants exhibited the same level of caution across all three scenarios: they do not accept digital outputs outright, and individual-level analysis shows this is a stable tendency rather than an averaging effect. This mix of enthusiasm and caution is similar to a large Australian study, where positive attitudes toward BIM coexisted with concerns about learning curves and the integration of BIM with AI (Ahankoo et al., 2025). However, this sample appears to be more cautious than other experimental studies that examined overreliance on AI, in which people accepted recommendations even when they were not fully correct (Buçinca et al., 2021; Vasconcelos et al., 2023). This may be a useful starting point, since calibrated trust in AI remains a major challenge for adoption in the AEC industry (Emaminejad and Akhavan, 2022). The scenario results also fit the cost-benefit view of reliance, where engagement with a tool output depends partly on the cost of verification (Vasconcelos et al., 2023): in scenario 1, the only alternative was a peer's recollection, so most students verified; in scenario 2, the instructor's warning offered a low-effort and socially safe alternative, so deference replaced verification; and in scenario 3, with two self-produced estimates and no external human input, responses were almost evenly split between verification and the manual method. Relying on authority under time pressure is understandable in a classroom, but it is different from the deliberate, evidence-based engagement with tool outputs emphasized in the overreliance literature (Buçinca et al., 2021), and this distinction matters when designing exercises. The attitude-behavior analysis adds another caution: no attitude item reliably identified students who accepted digital outputs, suggesting that direct decision exercises, rather than questionnaires alone, are needed to see how individual students respond when tool outputs conflict.

5.2. Gap between Awareness and Applied Skill

There is a second pattern between students' understanding and their feelings about their ability. The conceptual knowledge and display of strong sustainability attitudes were evident, and they also believed that tools could help evaluate environmental impacts. At the same time, only about one-third felt they could interpret hydrologic models. Fewer than one-third felt they could apply digital lessons in real settings, and a large majority felt less prepared when real experience is missing. This gap between knowing and doing is also discussed in the sustainability competencies literature (Brundiers et al., 2021; Redman and Wiek, 2021) and has been reported in BIM education, where the connection between university teaching and professional practice remains weak and inconsistent (Besné et al., 2021). Kolb's learning cycle offers a simple explanation: knowledge becomes practical ability through concrete experience and active experimentation (Kolb and Kolb, 2022).

Students seem to have the conceptual foundation, but their actual experience with hydraulic modeling and BIM is limited. The exploratory results point in the same direction. Breadth of exposure predicted nothing, while the small group with hydrology exposure reported much better model interpretation. Although this result should be viewed with caution, given the small subgroup and potential self-selection, it suggests that sustained use of specific tools may matter more than mere exposure to many tools. Similar gains in both conceptual understanding and technical skills have been reported in hydrology and water resource courses (Byrd et al., 2022). Overall, students already understand the value of environmental modeling; what they seem to lack is practical confidence in using it.

5.3. BIM Exposure Gap

The third pattern concerns BIM specifically. With only 8.2% of respondents reporting BIM exposure, the BIM-related sustainability item collected mostly neutral answers, and scenario 3 produced the most divided decision profile. Given the documented efficiency potential of BIM-based lifecycle assessment for environmental evaluation (Zimmermann et al., 2021) and the growing dominance of embodied emissions in building life cycles (Röck et al., 2020), the low exposure observed here represents a missed opportunity. Introducing BIM earlier and pairing it explicitly with lifecycle analysis exercises would address both the exposure gap and the awareness-skill gap at once, and it would give programs a concrete, assessable point for sustainability integration of the kind that current curriculum reviews find difficult to measure (Nakad et al., 2024). The curricular actions that follow from this pattern and the two patterns above are set out in section 6.

5.4. Limitations

Several limitations bound the conclusions of this study. First, the data come from a single institution, so the exposure profile in Fig. 1, and in particular the low BIM and hydrologic modeling exposure, partly reflects the structure of one curriculum and may not generalize to programs that sequence these tools differently. Second, all measures are self-reported perceptions; a student who reports being unable to interpret hydrologic models may be underconfident rather than incapable, and the reverse is also possible, so the skill gaps identified here should be read as perceived rather than tested competence. Third, the sample is concentrated in the sophomore and junior years, with only eight seniors and one graduate student, which prevented meaningful comparison across the full academic progression, and the tool-specific exposure subgroups (eight

hydrology-exposed and six BIM-exposed students) are too small to support more than descriptive comparison. Fourth, the design is cross-sectional, so the association between tool exposure and perceptions cannot be interpreted causally; exposure is self-selected, and cohort effects cannot be disentangled from exposure effects. Fifth, the instrument was assembled from literature themes rather than adopted from validated scales, and several item groups showed modest internal consistency because they deliberately combine favorable and cautionary statements; the analysis was therefore kept at the item level, and formal validation of the instrument, including its factor structure in a larger sample, is needed before composite scoring. Sixth, the supplementary analyses involve families of eight or more related tests reported with uncorrected p-values. They are offered as exploratory patterns for replication, not as confirmed effects. Finally, the three decision scenarios were forced-choice classroom vignettes. They capture stated intentions under hypothetical conditions, and behavior on a real project under real schedule pressure may differ. In addition, the short completion time means that some responses may reflect limited deliberation, and, without a known distribution of counts, nonresponse bias cannot be ruled out.

6. Recommendations

Based on findings from a single university, five recommendations can be made for civil engineering programs. These have not been tested by us as valid solutions, so the level of empirical support for each is noted. First, programs should focus on deeper learning of fewer digital tools rather than broad exposure. The number of tool categories experienced was not significantly related to any outcome, while the eight students who used hydrological modeling tools rated their interpretation ability higher than other students. Hydrological modeling, where only 32.9% agreed they could interpret models, and BIM, which had only 8.2% usage, are two possible areas for deeper instruction. Second, BIM could be introduced earlier and linked with lifecycle content. In the full sample, 54.8% were unsure whether BIM improved their understanding of waste management, while 89.0% agreed that digital tools help assess environmental impact. An early BIM module using a lifecycle assessment exercise could address both. Third, simulation-based learning should include a physical component, such as a laboratory activity, a field trip, or a project. Most students supported combining realistic activities with simulations (93.2%) and emphasized hands-on learning (86.3%), yet only 28.8% felt confident applying digitally learned skills in real situations. Asking students to compare simulated results with actual measurements or hand-calculated values may help this transfer. Fourth, verification should be taught as a separate skill. Scenario results showed that students verified when no alternative was available but deferred when an instructor's answer was provided, while only 58.9% felt prepared to justify decisions made with digital tools. Instructors could occasionally withhold answers and assess students' reasoning with a rubric. Finally, student decision behavior should be assessed directly rather than through attitude questions alone. This recommendation is exploratory and based on uncorrected correlations, but no attitude item identified students who accepted digital tool outputs without question. Short scenario tasks could provide a low-cost complement to questionnaires, while using multiple assessment methods is also consistent with recommendations for evaluating sustainability integration (Nakad et al., 2024).

7. Conclusion

This study surveyed 73 students in civil engineering courses. Most of the participants were undergraduate sophomores and juniors, and the study examined links between exposure to digital construction technologies, sustainability awareness, and decision-making. Students generally viewed digital tools positively while maintaining professional responsibility, strong sustainability awareness, and a verification-oriented decision-making style: 83.6% did not accept the digital output in any of the three scenarios, and verification behavior was consistent across individuals and scenarios. Three gaps emerged: limited ability to interpret hydrologic models, weak transfer of digital learning to real settings, and very low BIM exposure, which limited students' ability to connect BIM with sustainability outcomes. Breadth of tool exposure was unrelated to these outcomes, while exposure to the specific relevant tool was associated with much higher self-assessed capability in the one subgroup large enough to examine. This suggests that simply adding more tools is not enough; curricula should integrate sustainability and digital tools more closely, introduce BIM and hydrologic modeling earlier and in greater depth, and strengthen verification and interpretation skills alongside tool use.

These conclusions also point out the work that should be done. Replicating the survey across institutions with different curricular sequences would test the exposure-perception relationship with real variation in when and how deeply tools are taught, rather than the breadth-only measure available here. Larger samples would also give the tool-specific comparisons that produced the most suggestive result in this study adequate power. Perception data should be paired with objective assessments, for example, asking students to actually interpret a hydrologic model output or reconcile a BIM and a manual quantity takeoff, so that the gap between confidence and competence can be measured directly rather than inferred from self-report. Pre-post designs built around specific tool-based courses would establish whether structured instruction shifts both sustainability awareness and decision behavior, and extending the sample to senior-year and graduate students, with longitudinal tracking into early career, would show whether the verification-oriented style observed here survives contact with industry deadlines. The scenario instrument itself can also be extended: varying the source of the conflicting human input (peer, instructor, supervisor), the stakes, and the time pressure would separate genuine verification habits from deference to authority, a distinction the present data raise but cannot resolve, and would test the cost-benefit account of reliance (Vasconcelos et al., 2023) in an engineering education setting. Together, these study designs would help confirm whether the patterns observed here hold under more rigorous testing.

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Author Contributions

Rizwan Farooqui contributed to conceptualization, methodology, validation, analysis, investigation, manuscript editing, visualization, supervision and project administration. Abid Hassan contributed to methodology, software, validation, analysis, investigation, data collection, draft preparation and visualization. Muhammad Khalid contributed to conceptualization, methodology, data collection and manuscript editing. Syed Ahmed contributed to validation, analysis, investigation, manuscript editing, and project administration.

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Institutional Review Board Statement

Formal IRB review was not sought prior to data collection. The survey was an anonymous, voluntary questionnaire on educational perceptions administered to adult students, and no personal or identifying information was collected.

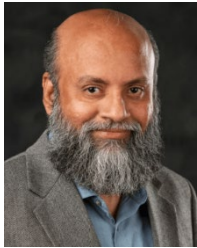
Declaration of Artificial Intelligence (AI) Tools

The authors used ChatGPT (Model GPT -5.6 Sol) only for language editing and formatting assistance. The authors reviewed and take full responsibility for all content.

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