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Construction Management Alumni Assessment of Digital Technology Importance, Impact, and Enablers

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Digital transformation is advancing in construction, yet evidence on how early-career professionals prioritize specific technologies and adoption conditions remains limited. This study surveyed alumni (2014-2024) from an undergraduate construction management program (58 complete responses) to examine perceived current importance of key digital technologies, expected five-year impact, and perceived barriers and deterrents to adoption, with comparisons by experience band and skill-acquisition pathways. A cross-sectional Qualtrics questionnaire collected Likert ratings of technology importance and barrier frequency, plus multi-select items on future high-impact technologies, sources of digital skills, and valued software features. Analyses included descriptive statistics, Relative Importance Index (RII) rankings, an exploratory Horizon Gap Index (HGI) contrasting normalized current importance with "top three" future salience, and point-biserial correlations linking barriers to discouraging factors. BIM/VDC ranked highest in current importance, while AI showed the largest positive horizon gap; most other technologies exhibited negative gaps, indicating stronger current embeddedness than future salience in the selection format. The most frequently reported constraints related to training, time, cost, and organizational support, with barrier–discouragement associations suggesting co-occurring resource and capability limitations. Alumni most often reported self-directed learning and prioritized integration and mobile accessibility, supporting implications for targeted training, mentorship, workflow standardization, and curriculum alignment with practice needs.

Keywords: Digital technologies in AEC, Construction Education, BIM/VDC adoption, AI in Construction, CM Perception Analysis

Introduction

Digital transformation continues to reshape construction through building information modeling/virtual design and construction (BIM/VDC), artificial intelligence (AI), reality capture (drones, lidar), immersive visualization (AR/VR/MR), robotics/automation, and connected sensing (Brozovsky et al., 2024; Elkhayat et al., 2024; Sharma Bhattarai & Kisi, 2024). While many tools now show clear value for coordination, quality, and decision-making, routine job-site use remains uneven due to fragmented data environments, limited interoperability, cost and time pressures, and capability gaps (Trask & Linderoth, 2023; Vararean-Cochisa & Crisan, 2025). AI is increasingly positioned for planning, control, risk, safety, and facilities, yet implementation is constrained by data readiness, integration with legacy systems, explainability, and workforce skills (Adewale et al., 2024; Chen et al., 2025; Datta et al., 2024; Egwim et al., 2024). Parallel advances in reality capture and immersive visualization show promise for progress tracking, verification, and experiential learning, but adoption still depends on investment, training, and workflow alignment(Al-Omari et al., 2023). BIM/VDC remains the most institutionalized capability, although adoption quality varies across markets and teams and continues to be limited by awareness, training, and standardization/interoperability challenges (Wang et al., 2023; Zahedi et al., 2022). Construction 4.0 research likewise emphasizes that value is mediated by people–process–technology alignment and organizational readiness rather than tool availability alone (van der Heijden, 2023).

A recent baseline study (Bhattarai et al., 2025) assessed construction management students' familiarity, expectations, and barriers across major digital technologies and reported strong expectations for drones and AI alongside recurring constraints related to training, cost, time, and limited curricular emphasis. However, student perceptions do not fully represent the conditions faced after graduation, when professionals must apply tools under production schedules, firm standards, and client requirements.

Research Gap and Study Focus

Despite growing adoption research, there is limited evidence on how early-career alumni prioritize technologies in current practice, which tools they view as most consequential over the next five years, and which barriers and deterrents are most salient once they transition into live project environments (Ghanbaripour et al., 2024; Saiba et al., 2025). Prior work also rarely links alumni perspectives back to student baselines to assess where expectations converge or diverge after entering industry, particularly as AI and related workflows evolve rapidly (Datta et al., 2024). In addition, actionable guidance remains under-specified on how training design, mentorship/onboarding, standardization and integration goals, and client-facing practices can be aligned with the constraint's alumni encounter (Al-Omari et al., 2023; Elkhayat et al., 2024; Wang et al., 2023; Xu et al., 2024).

Accordingly, this study addresses four research questions:

- RQ1: Which digital technologies do alumni perceive as most important in current practice?
- RQ2: Which technologies are most frequently selected as high impact over the next five years, and how does this compare with current importance (HGI)?
- RQ3: What benefits, software features, and skill-development pathways do alumni prioritize?
- RQ4: Which barriers and discouraging factors tend to co-occur, and how do patterns vary by experience band and relative to the prior student baseline?

Methodology

A quantitative, cross-sectional survey design was employed using an online questionnaire (Qualtrics). The sampling frame comprised alumni of a construction management program graduating between 2014-2024 (approximately 800 graduates). An invitation email was distributed to the alumni list; 73 alumni initiated the survey, and 58 complete responses were analyzed. Of the 73 alumni who initiated the survey, 58 provided complete responses across the core modules (technology ratings, barriers, and practice-context items) and were retained for analysis. The remaining 15 partial submissions were excluded because they did not provide sufficient data to compute the study's primary indices (RII, HGI) and barrier-discouragement associations on a consistent denominator. Participation was voluntary and anonymous, and institutional review board (IRB) approval was obtained.
The instrument included four modules: (1) Demographics (experience band: <2, 2–5, 6–10, ≥10; role; sector); (2) Technology importance/benefits (10 technologies rated 1–5; project benefits selected); (3) Barrier frequency (training, cost, time to learn, management support, field resistance, mentorship, standardization/interoperability, cultural resistance, and skilled labor availability; Never-Always); and

(4) Practice context (top-three future-impact technologies; discouraging factors; skill sources; valued software features; plus four Likert items on preparedness/support/career impact/confidence).
Relative Importance Index (RII) (Bhattarai & Kisi, 2022) was used to rank technologies:

$$RII = \frac{\sum_{i=1}^{N} w_i}{A \times N}$$

where $w_i \in [1,5]$, A=5, and N are valid responses.

Future impact was measured using a "top 3" selection item, producing P_j^{future}, the proportion of respondents who selected technology $j$as a high-impact technology (0–1). Current importance was measured via 5-point Likert ratings and normalized as $P_j^{current} = \bar{w}_j/5$. An exploratory Horizon Gap Index was computed as:

$$HGI_j = P_j^{future} - P_j^{current}$$

Because $P_j^{future}$is selection-based while $P_j^{current}$is rating-based, HGI is interpreted descriptively.

Barrier-discouragement relationships were screened using point-biserial correlations (Pearson r between barrier ratings and 0/1 discouragement selections). |r|>=0.25 (moderate-or-greater magnitude) were emphasized and interpreted as exploratory study given multiple comparisons. Experience-related patterns were examined via cross-tabulations with standardized residuals as effect-size diagnostics.

Results and Analysis

58 complete responses were taken for data analysis. Experience was broadly distributed across career stages: Less than 2 years (24.1%), 2-5 years (37.9%), 6-10 years (31.0%), and more than 10 years (6.9%), which enabled contextual comparisons in analyses. Respondents' roles reflected project delivery functions such as superintendent (22.4%), project engineer (17.2%), project manager (15.5%), field engineer (8.6%), assistant project manager (8.6%), estimator (8.6%), director (6.9%) and other titles accounted for the remaining responses (12.1%). Responded sectors were led by commercial (60.3%), followed by residential (13.8%), heavy civil (12.1%), and industrial (12.1%) and one respondent indicated another/unspecified sector. The number of participants predominantly comprises project-facing positions in commercial construction, having satisfactory variations for diversified reporting however, smaller groups in specific positions and industries necessitate careful assessment.

Significance of Digital Technologies

The Likert distributions and RII show a clear prioritization of technologies. BIM/VDC ranked first (RII = 0.77) with ratings concentrated at 4-5. Drones (0.63) and AI (0.61) followed, with substantial high ratings but more dispersion than BIM/VDC. A second tier comprised Lidar (0.53) and IoT/sensors (0.49) with more mixed responses. Robotics/Automation (0.44) and AR/VR/MR (0.42) ranked lower, indicating less consensus on importance.

Table 1. Significance of Digital Technologies

Digital Technologies	**1**	**2**	**3**	**4**	**5**	**RII**	**Rank**
BIM/VDC	6	6	7	10	29	0.77	1
Drones	12	9	10	11	16	0.63	2
AI	16	9	5	11	17	0.61	3
Lidar 3D Scanning	20	9	11	8	10	0.53	4
IoT/Sensors	25	6	10	10	7	0.49	5
Robotics/ Automation	29	9	8	3	9	0.44	6
AR/VR/MR	30	11	5	4	8	0.42	7
Blockchain for Project Management	35	9	5	6	3	0.37	8
Digital Twins	39	4	7	4	4	0.36	9
Additive Manufacturing	36	10	6	2	4	0.35	10

Project Benefit from Using Digital Technologies

Stacked bars (Figure 1) summarize how reported advantages are distributed across experience bands. Across most advantage categories (efficiency, communication, and accuracy), responses are concentrated among alumni with 2–5 and 6–10 years of experience, while fewer selections come from the <2 years and ≥10 years groups. Safety-related benefits appear more frequently among the <2 years group, whereas cost savings are reported primarily by the more experienced bands (6–10 and ≥10 years). Given uneven group sizes, Figure 1 is interpreted as a descriptive comparison rather than evidence of statistically significant differences.

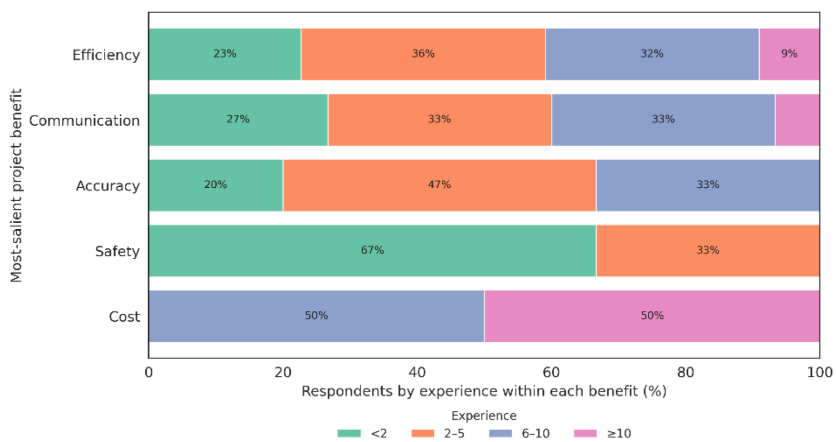

Figure 1. Project Benefit by Experience

Sources of Digital Skills and Preferred Software Features

Alumni most frequently reported acquiring digital technology skills through self-directed/online learning (71%), followed by employer-provided training (53%) and university courses (48%); peer mentorship (33%) and industry workshops/certifications (24%) were less common. Because respondents span multiple graduation cohorts, these aggregate rates may mask cohort effects (e.g., more recent graduates reporting greater reliance on university coursework). Overall, Figure 2 shows a hybrid learning ecosystem in which self-paced resources dominate while workplace programs and formal coursework provide substantial complementary pathways.

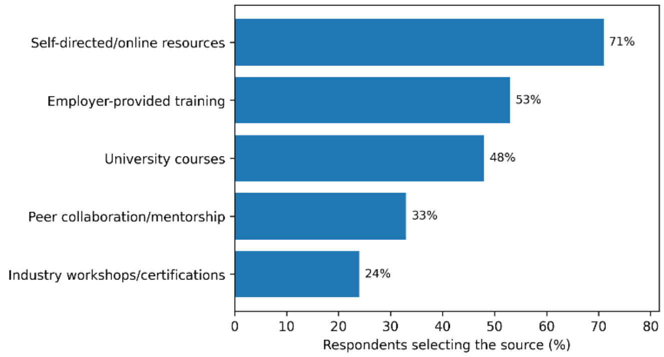

Figure 2. Sources of digital technology skill acquisition (multi-select; N=58)

The alignment of preferences for digital technology features with acquisition patterns and fieldwork realities is illustrated in Figure 3. Respondents prioritized integration with other tools (30%) and mobile accessibility (23%), indicating a strong emphasis on seamless data flow across platforms and reliable use in site conditions. Collaboration features (17%) and automation/AI capabilities (17%) form a second tier, emphasizing real-time coordination and efficiency gains in routine tasks. Customization options (13%) rank lower but remain material for tailoring workflows to project or firm standards. The pairing of self-directed learning with a demand for integrated, mobile, and collaborative toolsets indicates a workforce that advances skills independently while expecting software ecosystems designed to minimize friction, enable coordination, and increasingly embed intelligent assistance.

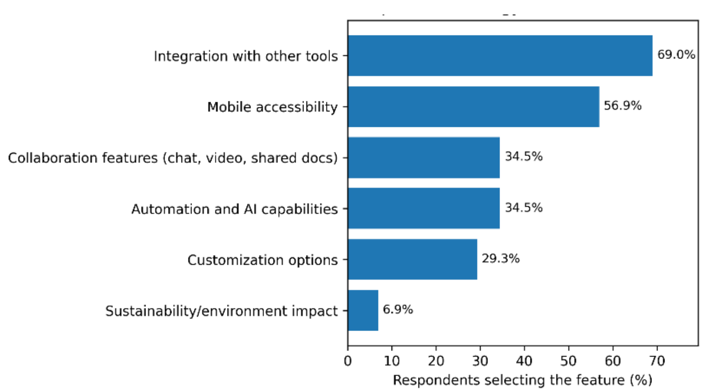

Figure 3. Valued workplace technology features (multi-select; N=58)

Barrier Severity and Discouraging Factors

Figure 4 links barrier frequency (1-5) with discouraging factors (0/1; select-all-that-apply) using point-biserial correlations (r). Figure 4 shows all barrier–discouragement connections; thicker links indicate larger |r| and color indicates sign (positive vs. negative). The strongest positive associations were high cost-low awareness (r=+0.41), high cost-limited resources (r=+0.34), lack of training-Low awareness (r=+0.33), and cultural resistance-traditional methods (r=+0.32), indicating constraints that tend to co-occur. Notable negative contrasts included skilled labor shortage-low client demand (r=-

0.32) and skilled labor shortage-data security (r=-0.25), suggesting distinct deterrent profiles rather than a single underlying barrier. Barriers and discouragers capture related content using different response formats, these associations are interpreted as exploratory indicators of co-occurrence and contrast, not evidence of latent structure.

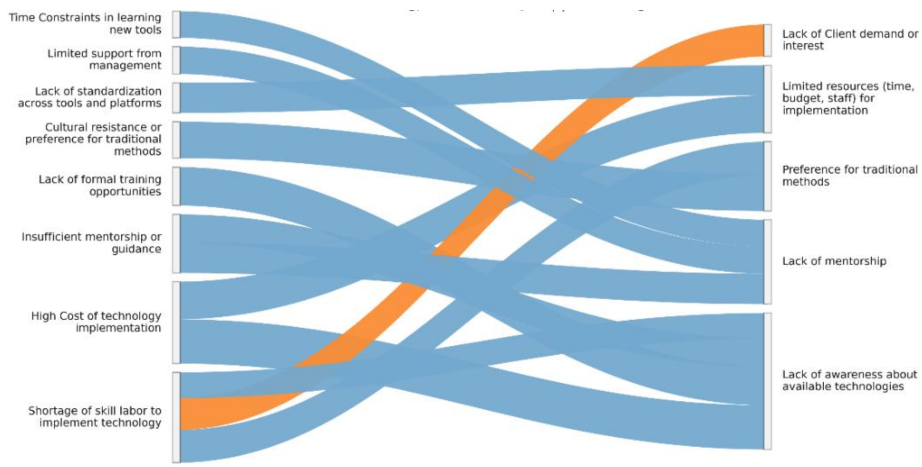

Figure 4. *Barrier Discouragement Concordance Analysis*

Horizon Gap Index (HGI) of Technology in Current Importance to Future Impacts

To contrast what alumni, view as important today with what they expect to matter most over the next five years, Figure 5 reports the exploratory HGI, contrasting five-year 'top-three' selection salience with normalized current importance; positive values indicate relatively higher future salience, while negative values indicate comparatively stronger current embeddedness. Figure 5 shows AI as the only technology with a positive gap (+0.20), indicating stronger expected future impact relative to its current importance. All other technologies exhibit negative gaps, most notably IoT/Sensors (-0.42) and BIM/VDC (-0.12), with additional negative values for AR/VR/MR (-0.13), Robotics/Automation (-0.15), and Drones (-0.26). These negative gaps likely reflect technologies perceived as important today but less frequently identified as future differentiators within a constrained top three selection format.

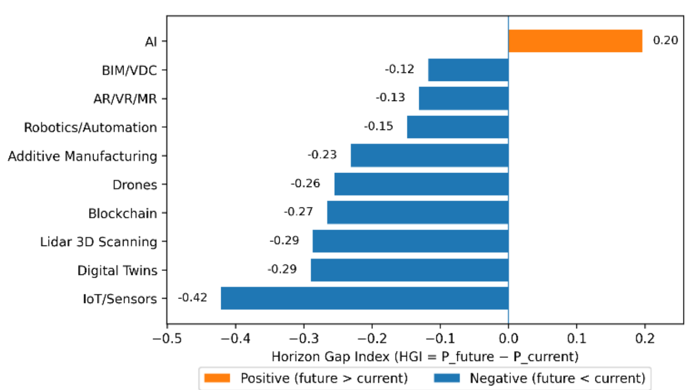

Figure 5. HGI comparing selection-based future salience to normalized current importance

Perceived Academic Preparation Gaps

Figure 6 presents a vertical bar chart summarizing how many respondents selected each topic as an area academia should have emphasized more. Out of 58 industry practitioners, Data analysis and digital project management was the most frequently endorsed gap (n = 32), followed closely by hands-on training with digital tools (n = 31) and real-world case studies of technology implementation (n = 29). A smaller, but notable, share pointed to changing management and technology adoption strategies (n = 14). This distribution indicates a clear preference for more practice-oriented, data-driven, and applied learning experiences, with nearly half or more of the sample prioritizing those top three areas. These alumni rankings provide a straightforward basis for targeting future course design and program revisions toward the skills they felt were lacking.

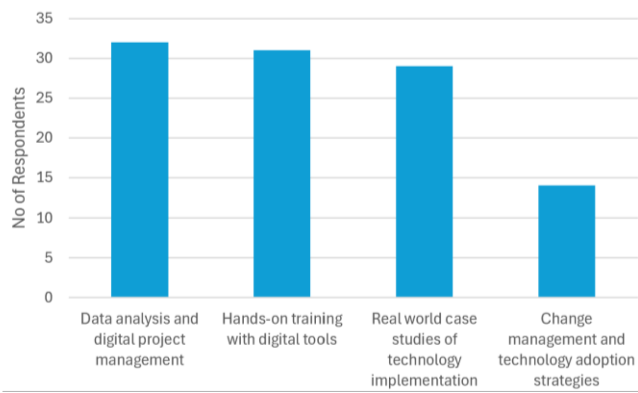

Figure 6. Perceived Academic Gaps

Discussion

Comparing Alumni and Student Perceptions

Alumni perceptions largely mirror the earlier student baseline (Bhattarai et al., 2025) regarding both priority technologies and adoption constraints. BIM/VDC remains the dominant operational foundation (highest RII), while reality-capture tools (drones and lidar) are generally viewed as important but appear more sensitive to work context and field workflows. AI is consistently identified as high-impact, although respondents' selections and barrier patterns suggest that its use is contingent on data readiness and integration capacity. The Horizon Gap results indicate comparatively higher future salience for AI, while several currently emphasized tools (e.g., IoT/sensors, drones) show lower future salience in the top-three format, suggesting that continued growth may depend on tighter integration with modeling, analytics, and standardized workflows. Compared with students, alumni place greater emphasis on practical deployment needs, particularly interoperability and mobile accessibility, reflecting day-to-day production demands. Barriers remain stable across groups (time, cost, training), but alumni more frequently highlight the role of management support, mentorship, and standardization as enabling conditions for sustained adoption.

Implications for Academia and Industry

The results point to several practical implications for easing the education-to-industry transition, but these should be interpreted as respondent-informed recommendations rather than causal prescriptions. Given that cost, time, and training were repeatedly identified as constraints, respondents' feedback suggests that stakeholders could explore cost-sharing mechanisms (e.g., coordinated licensing or access programs among employers, vendors, and universities) to reduce friction in early-career tool continuity. Consistent with alumni emphasis on integration and mobile accessibility, respondents also highlighted the value of standardized data structures and workflows that enable interoperability across platforms, which aligns with prior work emphasizing standardization as an enabling condition for adoption (Abanda et al., 2025). Because many alumni report self-directed learning, the findings further suggest that organizations and academic programs may benefit from supporting that behavior through short, blended learning modules, protected practice time, and structured mentoring, approaches that have been recommended in transportation-sector guidance and AEC change-management literature (Dylla, 2019). Finally, the descriptive "benefits-by-experience" patterns indicate that role-targeted training may be useful (e.g., safety- and field-execution emphasis for early-career roles; coordination and planning applications for mid-career roles; cost and controls applications for senior roles), and that emerging capabilities should be linked to role-relevant outcomes and evaluated through phased pilots with clear KPIs and leadership sponsorship-practices commonly associated with more durable adoption efforts in AEC settings (Elgamal et al., 2025; Maali et al., 2020).

Limitations and Future Research

Several limitations should be considered when interpreting these findings. First, the sample reflects alumni from a single U.S. construction management program and a voluntary response process (58 complete responses from an approximately 800-person cohort), which limits generalizability and introduces potential non-response bias toward more engaged or digitally inclined alumni. Relatedly, only complete submissions were analyzed because partial responses did not provide sufficient data to compute the primary indices (RII/HGI) and barrier–discouragement associations on a consistent basis. Second, all measures are self-reported and cross-sectional, and may be affected by recall and social desirability effects. Third, the Horizon Gap Index combines rating-based current importance with selection-based future salience and is therefore interpreted as an exploratory indicator rather than a causal or effect-size measure. Finally, because the study reflects one program context, the observed skill-gap patterns may be institution-specific and should be interpreted as descriptive evidence rather than sector-wide estimates.

Future research should extend this work beyond a single university by surveying alumni across multiple institutions and regions to assess whether the observed priorities and skill gaps replicate nationally. Mixed-method designs that incorporate interviews and longitudinal follow-up would further contextualize perceived benefits and barriers as tools and workflows mature. In addition, incorporating organizational and project context (e.g., firm size, delivery method, procurement constraints, IT governance) and, where feasible, triangulating perceptions with employability outcomes and employer feedback would strengthen evidence on curriculum–practice alignment.

Conclusion

This study strengthens prior research on the digital technology readiness of construction management students by investigating the perspectives of recent alumni. This follow-up study consolidates a practice-proximal view of digital adoption among recent construction management alumni, showing that value creation hinges less on adding tools and more on aligning data pipelines, workflows, and organizational supports. Evidence from importance rankings, future outlooks, barrier-discouragement structures, and skill-acquisition pathways indicates a maturing digital core alongside emerging opportunities where immersive and automated methods can expand impact when embedded within interoperable, mobile, and user-centered ecosystems. For industry and academia, the actionable priority is capability building at the interfaces: standardizing information exchanges, reserving protected time and mentorship for upskilling, and translating data-centric methods into hands-on, case-based learning. Strategic pilots should target high-leverage workflows where immersive visualization and automation can demonstrably reduce errors and cycle time. Future research should extend these practice signals with multi-institution cohorts and longitudinal tracking, linking curricular interventions and organizational enablers to measurable performance outcomes and career progression.

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