Industry Perception of the Knowledge and Skills Required to Implement Sensor Data Analytics in Construction

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Abstract: Construction, one of the largest industries in the world, consistently underperforms and faces barriers in leveraging the full potential of applying analytics to sensor data due to a lack of a skilled workforce. The prospects for data-driven solutions to address emerging construction challenges and enhance performance across project life cycles are therefore constrained. Through mixed-method research utilizing a survey and focus group, this study investigates the knowledge and skills required for graduating construction engineering and management students to implement sensor data analytics in the construction sector. The findings revealed that sensor data analytics knowledge and skills are required to systemically process and analyze data from sensing technologies and present them in formats for effective decision-making. The presented key knowledge areas, specific skills, and their significance can aid the construction industry and academics to streamline professional development efforts to match the actual demands, allowing for more efficacy in workforce training. The future construction workforce is expected to gain a competitive edge with sensor data analytics knowledge and skills as the ubiquitous integration of sensing technologies continues to drive the tremendous growth of sensor data. **DOI: 10.1061/JCEECD.EIENG-1902.** *© 2023 American Society of Civil Engineers.*

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Introduction

The United States (US) has remained one of the most dominant figures in the global construction business, with US construction companies contributing 4.1% to the nation's GDP (BEA 2022). Construction generates a significant annual expenditure of $1.78 trillion (US Census Bureau 2022), and the labor force is predicted to grow 4.3% by 2030 (BLS 2021). However, a declining rate of productivity accompanied by the slow adoption of new technologies continues to have a detrimental impact on the industry's safety performance, quality of work, and workforce retention (Huang et al. 2009).

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To curb the aforementioned drawbacks of the industry, researchers and practitioners have begun to explore the potential of sensing technologies such as laser scanners, cameras, drones, global positioning systems (GPS), ground penetrating radar (GPR), radio frequency identification (RFID), and inertial measurement unit (IMU) (Arabshahi et al. 2021; Zhang et al. 2017). From intelligent control systems for infrastructure monitoring to smart construction designs that can influence construction dynamics through the optimization of resource utilization, the practical implications for sensing technologies are extensive. These technologies have continued to offer innovative breakthroughs that can drastically change the way construction data are produced, tracked, and shared, with visible improvements in construction performance (Ellis 2020). Construction companies, such as Skanska, Bechtel, Davis, Choate, Balfour Beatty, and DPR, have systematically integrated various sensing technologies into their project delivery processes. These companies are employing data analytics to process data from sensing technologies, analyze the data, and present the results in formats suitable for decision-making. For example, location coordinates from GPS data can be analyzed to infer contextual information that can support high-level decision-making regarding the type, quantity, and capacity of construction equipment (Louis and Dunston 2018). Similarly, analysis of image-based data from cameras and laser scanners can support safety managers' decisions regarding compliance with OSHA regulations such as the use of personal protective equipment and protection of exposed reinforcing bars (Yi and Qu 2021). Industry reports such as the one from the World Economic Forum have predicted that the rate of adoption of advanced sensing and analytics techniques could result in significant annual global cost savings of 13%–21% in the design and construction phases and 10%–17% in the operations and maintenance phase (WEF 2016).

Despite these benefits, the practice of analytics on sensor data is still in its infancy in the construction industry. This could be attributed to the shortage of skilled workforce with construction-related backgrounds, equipped with the knowledge and skills in this area (Mansouri et al. 2020). This is significant as it is increasingly being recognized that a workforce with a construction-related background is better positioned to address the industry's challenges because of their knowledge and grounding in the domain field. However, little is known or has been formalized about the knowledge and skills that are required for graduating construction students to implement sensing technologies and sensor data analytics in the construction industry.

Knowledge and skills are necessary human capital for advancing and sustaining innovation in any industry sector. In construction, these are necessary for delivering timely, safe, and quality projects (Ahn et al. 2012). The knowledge and skill sets required for advancing innovation with sensing technologies in the construction industry are embedded in the workforce and are acquired through some form of education (e.g., training) and experience. Industry practitioners are constantly exposed to these new technologies, and they develop themselves to be aware of the emerging practices and to secure transportable human capital for better opportunities (Johari and Jha 2020). Therefore, it is appropriate to elicit the opinions of industry practitioners regarding the knowledge and skills that are significant for preparing the future workforce to advance innovations with sensor data analytics.

The objective of this research is to identify the knowledge and skills required of the future workforce to implement sensor data analytics in the construction industry. To achieve this, this study investigates industry practitioners' perception of the specific knowledge and skills required of construction engineering students for implementing sensing technologies and performing analytics on the sensor data, the extent to which the future workforce is equipped with the skills utilized by construction practitioners, and the value of and anticipated demand for these skills by the prospective employers. The paper is structured as follows: First, a literature review is presented to provide background to the study. This is accompanied by the methodology, i.e., survey and focus group discussions with construction industry practitioners, and results of the methodology. This study contributes to the body of knowledge from two perspectives: (1) identifying the knowledge and skills required to implement sensing technologies and sensor data analytics in the construction industry and (2) highlighting the value of the identified skills and their anticipated demand in the construction industry. The findings can inform educational programs to better align with the demands of modern technology-driven construction practices, ultimately improving their competitiveness in preparing the workforce for the future.

Background

Sensing Technologies in the Construction Industry

Construction is a highly information-intensive and dynamically functioning sector where it is challenging to achieve the requirements of modern construction management using traditional or manual methods of data acquisition (Shen and Lu 2012). Cheng et al. (2011) reported that sensing technologies could accurately produce as-built data, reduce nonvalue-added operations, and enable rapid actions to safety issues, all contributing to improved time-cost benefits. Sensing technologies are generally classified as nonvision or component-based (e.g., GPS, RFID, and IMU) and vision-based (e.g., laser scanners, cameras, photogrammetry, and drones) (Guven and Ergen 2021). A diverse range of sensing technologies is emerging on construction job sites to capture dynamic operational information to support swift decision-making. For example, Skanska has utilized Vela Systems to track approximately 3,000 RFID-tagged precast concrete components and incorporate them into BIM models during the construction of the New Meadowlands Stadium (Miller 2008). Balfour Beatty implemented GPS to track electrical components in precast concrete and RFIDs in personnel's PPEs to track safety compliance on the Capitol Crossing project (Balfour Beatty 2016). Bechtel was among the first to combine a drone with a supporting technological platform to collect real-time data and perform data analytics to increase construction productivity in large-scale projects (Bechtel 2015). Similarly, DPR Construction employed drones to capture images of the job sites and incorporate them into project planning and progress tracking (D. P. R. Construction 2014). Researchers have also achieved promising results from applying sensing technologies in construction. For example, Yan et al. (2017) demonstrated the potential of IMU to provide information on the extent of workers' ergonomic exposures that can help reduce work-related musculoskeletal injuries. Bosche et al. (2009) implemented laser scanners for tracking the progress of construction work. These studies further demonstrate the significance of sensing technologies for improving the situational awareness of project teams through access to real-time proactive information to effectively address productivity and safety challenges. The use of sensing technologies in construction, whether through worker wearables or in a full-fledged project context, has contributed to increased efficiency, safety, and cost-effectiveness in the industry and is expected to grow as technologies evolve.

Sensor Data Analytics in Construction

It is apparent that sensing technologies are gaining traction in the construction market which demands an understanding of how to analyze the stream of raw sensor data in a structured manner to deliver relevant insights (Boje et al. 2020). As an emerging research topic, data analytics has been referred to with a variety of definitions in both industry practice and academic research and in some cases used interchangeably with 'data analysis'. The term 'data analysis' refers to the processing of data using traditional theories (e.g., classical statistical, mathematical, or logical), analytical techniques, and tools to find relevant insights and inform decision making (Cao 2017). On the other hand, data analytics refers to the theories, technologies, tools, and processes that enable an in-depth understanding and discovery of actionable insight into data (Cao 2017). In summary, data analysis is a particular stage in the process of data analytics that entails examining and interpreting data to generate insights, whereas data analytics spans the whole process of working with data. Accordingly, sensor data analytics involves the features of various sensor data acquisition tools, processing, analysis, and interpretation techniques to affect the user's perspective to make the decision (Tsai et al. 2015). With additional specificity to construction, Mansouri et al. (2020) described construction-based data analytics as the examination of raw data obtained from construction projects to gather insights and make informed decisions for planning, execution, management, and control. For example, using data analytics approaches, data from GPS can be structured and analyzed to produce safety and productivity information that can help to make effective interventions (Aggarwal 2013). Hence, construction-based sensor data analytics is built on the concept of processing data collected from sensing technologies, evaluating the data, and presenting the data in formats that provide actionable insights (Akanmu et al. 2022; Louis and Dunston 2018). This is focused on the premise that sensor data analytics can be leveraged to enhance construction performance in various areas. For example, Pradhananga and Teizer (2013) demonstrated how location coordinates from GPS data can be processed and converted into formats that can help project managers plan, manage, and control equipment-related work. Lin et al. (2015) presented a framework for acquiring image data through UAV in order to perform visual data analytics on progress images, which can support as-built modeling and the coordination of construction projects with greater accuracy and completeness. Rashid and Louis (2020) employed machine learning techniques to examine motion data collected from IMU sensors and automatically determine the tasks carried out by articulated construction equipment.

Knowledge and Skill Requirements of Sensor Data Analytics

The adoption of new technologies and techniques into any occupational sector will place a demand on educational and industrial institutions to equip the workforce with the knowledge and skills to interact and advance innovation (Maurin and Thesmar 2004). Implementation of sensing technologies in the construction industry creates new practices or ways of delivering projects that demand higher-level skills (Calvetti et al. 2020). For example, to implement laser scanners on construction projects, the workforce will need to understand the context for the use of scanners, how to operate laser scanners and coordinate their safe implementation on construction sites, how to analyze data from the scanners and present the results in formats that aid decision making, and the cost implications of adopting scanners on projects (Shanbari et al. 2016). Although research on identifying a set of defined skills for implementing sensing technologies and sensor data analytics in construction applications is limited, some researchers have made efforts to highlight the skills relevant to advance the enablers of Construction 4.0. Construction 4.0 represents the fourth industrial revolution within the construction industry and encompasses various technological advancements, including sensing technologies and sensor data analytics. While the body of research in this area is still developing, these initial studies contribute to understanding the skill sets necessary for embracing and maximizing the benefits of these technologies within the construction sector. Both types of skills are presented in Tables 1 and 2.

Sensor and Data Analytics in Construction Education

The sheer volume of data produced by sensing technologies necessitates a command of data analytics skills and techniques to glean insights and improve productivity, efficiency, and self-management (Li et al. 2021). However, in traditional construction education, students are not prepared for sensor implementation or analytics. These can be even more challenging processes when embedded in construction processes, such as the implementation of GPS devices on various resources to collect data and analyze them for decision making. According to Hurlebaus et al. (2012), since most construction engineering students have little to no experience in the fields of sensor control or signal processing, it is necessary to teach the principles of sensing technologies in the context of domain applications. Among the few institutes that teach sensing technologies in the context of construction or civil engineering, the University of Illinois at Urbana-Champaign offers a course on 2D and 3D visual sensing for data acquisition and analysis of buildings and civil infrastructure systems to provide construction graduate students with a fundamental understanding of the concepts and applications (University of Illinois at Urbana-Champaign 2022). The University of Nevada at Las Vegas teaches a course on large-scale sensor analysis for construction management with an emphasis on unstructured data collection, preparation, processing, and interpretation (University of Nevada Las Vegas 2023). Lehigh University offers a course on the essential aspects of sensing technologies in civil engineering applications, with a focus on implementing them for structural systems (Zhang and Lu 2008). Texas A&M University offers a specialized course on smart structures focused on the use of sensor technologies to develop smart structural systems to equip students with the knowledge of smart materials and technologies and integration strategies (Hurlebaus et al. 2012). Western Michigan University offers a course on sensing and modeling technologies to teach students data processing and visualization methods for analyzing the data collected by various sensors (Western Michigan University 2016).

A report by Associated General Contractors of America (AGC) mentioned that 32% of the surveyed construction businesses were looking to incorporate sensing technologies (such as drones, laser

Table 1. Sensing technology implementation skills, descriptions, and corresponding publications

Labels	Skills	Descriptions/Examples of skills	Reference
ST1	Problem identification skills	Identification of risks or challenges to be solved by the sensing technologies	Blinn and Issa (2016), Bongomin et al. (2020), and Edum-Fotwe and McCaffer (2000)
ST2	Sensor selection skills	Ability to select suitable data acquisition/sensing technologies	Hou et al. (2022)
ST3	Technological competency	Ability to implement data acquisition/sensing technologies	Bae et al. (2022) and Marocco and Garofolo (2021)
ST4	Estimating skills	Ability to determine cost-effective sensing solutions	Love and Matthews (2019)
ST5	Scheduling skills	Ability to schedule sensor implementations to obtain data	Rao et al. (2022)
ST6	Safety skills	Understanding the safety implications of sensing solutions	Khalid et al. (2021)
ST7	Ethical skills	Knowledge and awareness of privacy and ethical conduct in sensor implementation	Khalid et al. (2021)
ST8	Problem-solving skills	Critical thinking and creative problem-solving skills with sensing technologies	Blinn and Issa (2016), Bongomin et al. (2020), and Edum-Fotwe and McCaffer (2000)
ST9	Collaborative skills	Ability to work in teams	Bayraktar and Ataç (2018)
ST10	Communication skills	Ability to verbally communicate ideas or solutions	Bayraktar and Ataç (2018)
ST11	Interdisciplinary application skills	Thinking across disciplines such as computer science, social science, and business management, to solve problems	Bongomin et al. (2020)
ST12	Adaptability	Ability to learn, risk management	Hou et al. (2022) and Low et al. (2021)

Table 2. Sensor data analytics skills, descriptions, and corresponding publications

Labels	Skills	Descriptions/examples of skills	Reference
SDA1	Safety skills	Understanding the safety implications of sensor data-related solutions	Zhou et al. (2015)
SDA2	Modeling skills	Two-dimensional (2D) and three-dimensional (3D) drawing and building information modeling	Bayraktar and Ataç (2018)
SDA3	Programming or coding skills	Coding in key languages (e.g., Python, C++, MATLAB)	Bayraktar and Ataç (2018)
SDA4	Problem formulation skills	Ability to describe or model a problem	Rambally (2017)
SDA5	Problem-solving skills	Logical reasoning, creativity, research, and analytical skills	Rambally (2017)
SDA6	Collaborative skills	Ability to work in teams	Bayraktar and Ataç (2018)
SDA7	Communication skills	Ability to verbally communicate ideas or solutions	Bayraktar and Ataç (2018)
SDA8	Interdisciplinary application skills	Thinking across disciplines such as computer science, social science, and business management, to solve problems	Madden et al. (2013)
SDA9	Ethical skills	Knowledge and awareness of ethical conduct with data handling	Ahmad et al. (2019) and Someh et al. (2019)
SDA10	Adaptability	Ability to learn, risk management	Gordon (2017)
SDA11	Data processing and analysis skills	Skills in Excel, MATLAB	Bayraktar and Ataç (2018)
SDA12	Presentation skills	Public speech, slides authoring, and visualization	Schneider et al. (2020)

scanners, and GPS-guided equipment) and that around half of the enterprises aim to increase their investment in information technology (AGC 2020). Although it has the most potential for future development, the construction industry still has the lowest degree of adoption of advanced data analytics associated with sensing technologies (Qi et al. 2020). Accordingly, the lack of training has been identified as the top barrier to upskilling the construction workforce in data analytics (Mansouri et al. 2020). Ogunseiju et al. (2021a) reported that there is a limited focus given to stand-alone courses on sensing technologies and that the majority of the courses have sensing technologies as course content. This results in a lack of emphasis on CEM workforce training on sensing technologies to ensure extensive coverage of industry applications, preventing future professionals from developing the required skills. There are also major disparities identified between conventional engineering education and the skills necessary to establish sensor data analytics-driven strategies needed for data selection, employment techniques, visualization, and communication of relevant conclusions to site practitioners (Gunay et al. 2019). From sensor technology implementation through sensor data analytics, it takes the entire experience (e.g., problem identification, sensor selection, modeling, data processing, and analysis) to get to the point where effective decisions can be made. The existing CEM curriculum either focuses on the deployment of data acquisition technologies or data analysis with prepackaged software to address a single application, leaving out the comprehensive problem-solving experience for the students (Akanmu et al. 2022). Furthermore, research is scarce on how sensor data analytics experiences should be integrated into the learning process to enhance students' knowledge and skills for industry practice.

Research Gap

The growth of sensing technologies is outpacing the development of the skill set required to fully exploit the data acquired and provide actionable intelligence in construction (Ahmed et al. 2018; Edirisinghe 2019). Accordingly, gaps can be observed in recent research and practice as (1) there is incredibly inadequate evidence of research examining the specific knowledge and skills required by the industry to advance with sensor data analytics; (2) due to the incredibly limited amount of information on knowledge and skills linked to sensor data analytics, academia and industry are unlikely to be cognizant of the actual limits and gaps in the construction domain; and (3) construction education programs have not effectively addressed the skills gap by taking into account the knowledge and skills that the industry demands. This study presents a comprehensive collection of knowledge and skills that hold potential for the advancement of construction education and industry. By understanding their significance, educators can foster the development of innovative learning strategies and gain direct benefits from their implementations.

Methodology

This research was streamlined with the approach to extract, understand, and formalize industry practitioners' perceptions of the skills required of graduating CEM students for implementing sensor data analytics in the construction industry. The overview of the research methodology is shown in Fig. 1. For the literature review, multiple databases (Google Scholar, Scopus, EBSCO, Engineering Village, Science Direct, and Web of Science) were searched to find pertinent papers on the application of sensor data analytics and sensing technologies in the construction industry. In the databases, the field labeled 'title/abstract/keyword' was extensively and systematically searched using relevant keywords such as skills, knowledge, sensor, sensing technology, data analytics, construction, safety, productivity, laser scanners, and GPS. Research articles, reports, and conference proceedings were included, and the search was restricted to the English language only. Based on the results, the articles were examined to find the information about skills indicated by sensors and data analytics. In addition to the literature review, the research adopted a mixed-method approach to obtain both qualitative and quantitative data (Creswell et al. 2007). Quantitative data were collected through questionnaire surveys and cross-validated with a focus group. The questionnaire survey was selected to generalize the opinion of industry practitioners (both current and prospective users of sensing technologies and sensor data analytics) regarding the knowledge and skills required of construction engineering students for implementing sensing technologies and performing analytics on the sensor data, the extent to which the future workforce is equipped with the skills utilized by construction practitioners, and the value of and anticipated demand for these skills by the prospective employers. The study protocol was approved by the Institutional Review Board (IRB # 21-278), and all participants were provided with informed consent information for the survey and focus group.

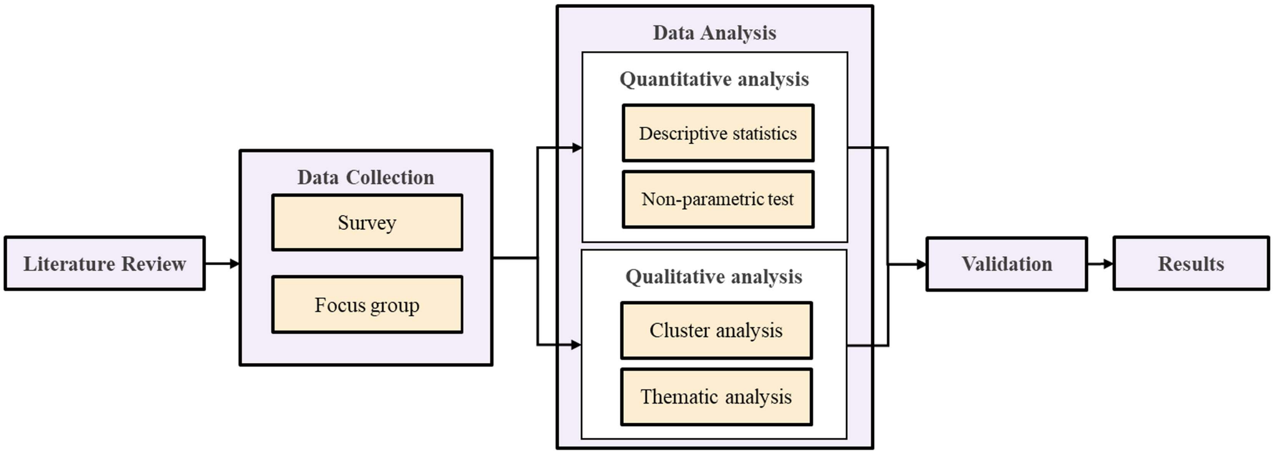

Fig. 1. Overview of research methodology.

Data Collection

Survey

The survey aimed to capture the perceptions of industry professionals regarding the skills required of graduating CEM students to perform sensor data analytics, the extent to which the skills are being performed by construction practitioners, and the value of and anticipated demand for these skills by prospective employers. The first section of the survey requested background information such as participants' age, gender, years of experience, and organization type and size. Through a combination of various question structures (i.e., open-ended, and closed-ended questions, multiple-choice entries, and a 5-point Likert scale), the survey requested participants' views on the specific skills and the extent to which these skills are being taught by institutions to implement sensing technologies and perform sensor data analytics. Factors investigated included types of sensing technologies, applications, and insights. Survey questions covered the current usage of these sensing technologies, the extent of skill preparedness, contracting mode (i.e., in-house or outsourced), and reasons for adopting the contract mode, and deployment length. Additionally, the influence of sensor data analytics on project decisions and the future adoption of sensing technologies were explored to better understand the value and projected demand of these skills.

The survey was developed and managed in Qualtrics, an online platform, and was designed to take about 7 min to complete. The survey was disseminated to potential participants by snowballing sampling techniques. The snowball method allows participants to relay the research instrument to their extended network for participation (Brickman Bhutta 2012). Data for the survey were collected both electronically and in person. Participants were contacted through university-industry contact lists and social media platforms such as LinkedIn, Twitter, and Facebook. There is no specific lead to where potential participants with specific experience with sensor data analytics can be found. Online social networking sites facilitated the process of not only efficiently sharing the survey but also constructing a snowball sample of small or specific subsets of the general population with the target expertise (Brickman Bhutta 2012). In addition, construction professionals were approached for in-person data collection during a career fair. The eligibility conditions were provided at the start of the survey, and participants were allowed to continue upon fulfillment of criteria such as (1) involvement with construction projects and (2) utilization of data acquisition/sensing technologies in the company or as part of other noncompany-related projects. The overall survey response data were acquired from June 2021 to February 2022.

Focus Group

To validate the results from the survey, a focus group was conducted with selected industry practitioners identified from the survey to be knowledgeable about the potential of sensing technologies and sensor data analytics and their implementation on construction projects. A focus group is a structured group discussion designed to elicit perspectives on specific topics in a controlled setting (Krueger 2014). The questions for the focus group discussion were formulated based on the survey and the accumulated responses. Construction industry practitioners who expressed their interest in participating were contacted and invited to the discussion. Five construction practitioners participated in the focus group session. Potential participants were identified through researchers' professional networks and communicated following approved IRB procedures. Prospective participants were contacted via email to describe the study, and they were screened according to the following inclusion criteria: (1) direct experience working with sensing technology and sensor data analytics and (2) involvement in decision making with sensor data analytics in US construction companies. Prior to the formal session, the participants were provided with electronic versions of a consent form and the interview question topics of the focus group discussion to familiarize themselves and enhance their preparation. Zoom was chosen to moderate the session as Falter et al. (2022) demonstrated that online focus groups on Zoom provide an overall positive experience for qualitative data collection. The focus group meeting was a 1-h session and was audio-recorded and transcribed. The lists of key knowledge areas and skills extracted from the survey were visually presented to the participants and their responses were requested.

Data Analysis

Survey

One hundred fifty-two individuals participated in the survey and served as the study's entire sample size since the professionals were considered to be experienced, and their participation ensured that the right viewpoints of the construction industry were documented. The survey data were analyzed using descriptive statistics, including response means and frequencies. To understand if there are differences in the responses of the practitioners with respect to their demographics (e.g., company size and experience level) and given that the data was collected on a Likert scale, a nonparametric test was conducted. Kruskal–Wallis test was employed to compare the means of the demographic groups since the data has more than two independent samples (e.g., 1–5, 6–10, 11–15, and above 15 years for experience level). A separate test was conducted for each skill set to identify if there were differences in the opinions of the different demographic groups. A p-value of less than 0.05 was considered to be significant. A post hoc test was conducted for instances where a significant difference was observed. All the statistical analysis was conducted using R studio and MS Excel. In addition, the open-ended survey questions were analyzed using thematic analysis. Open-ended survey questions offer a good approach to obtaining honest and diverse responses from subjects (Erickson and Kaplan 2000). The use of cluster analysis encourages the classification of subjects into different categories. This helps to identify distinctive characteristics in a dataset (Battaglia et al. 2015).

Focus Group

Upon review by participants, the focus group transcript was deidentified by assigning random numbers to each participant while excluding personally sensitive or identifiable information. Appropriate codes were assigned to the transcript using DeDoose, an application for analyzing qualitative data. Through open-coding, the emerging themes were identified based on appropriate comments from the responses (Saldaña 2009). The themes were primarily classified into two broad categories: knowledge and skills. The codes with relevant themes were integrated into meaningful clusters (Hsieh and Shannon 2005). Information pertaining to the theme of "Knowledge" in sensor data analytics, introduced codes such as sensing technologies' applications, insights, and the underlying challenges experienced while extracting insights. The theme of 'Skills' was categorized with child codes such as sensor implementation and data analytics skills. Categories with mutual concept representations (e.g., value and anticipated demands) were allocated to the main theme. Similar themes within each question from the focus group were identified to advance the categorization and summarization of the information. The extracted themes were cross-checked with the transcript to ensure consistency. Also, agreement with the codes was rated by two researchers, and the interrater agreement was a Cohen–Kappa of 0.75, establishing a substantial agreement. The credibility of the results was enforced by reaching an agreement between the researchers on the meaning of codes and the emergent themes (Miles et al. 2018; Robson and McCartan 2016).

Results

The results are organized into two main sections. The first section outlines the key findings of the industry survey, including presenting the specific knowledge and skills required to implement sensing technologies and execute sensor data analytics, the extent to which the industry utilizes the skills, and their value and anticipated demand. The second section presents qualitative results that were thematically coded from the focus group transcripts to validate the survey responses.

Survey Findings

Characteristics of Participants

Table 3 details the characteristics of industry practitioners, including their frequency and percentage distribution by gender, race, and industry involvement in terms of years of experience, type of construction, and company size. The survey's findings represent a sample of professionals from a wide range of demographic backgrounds.

Table 3. Characteristics of the surveyed industry practitioners

Measure	Frequency	Percentage (%)
Gender		
Male	122	80.3
Female	26	17.1
Nonbinary/third gender	2	1.3
Unidentified	2	1.3
Race		
White	111	73.0
Black or African American	11	7.2
Asian	12	7.9
Hispanic	11	7.2
Native Hawaiian or Other Pacific Islander	1	0.7
Other	6	3.9
Construction experience		
1–5 years	59	38.8
6–10 years	25	16.4
11–15 years	22	14.5
Above 15 years	46	30.3
Construction type		
Residential	88	39.6
Commercial	33	14.9
Specialized industrial	60	27.0
Heavy	28	12.6
Other	13	5.9
Company size		
Less than 10	2	1.3
10–19	6	3.9
20–49	5	3.3
50–99	10	6.6
100–249	22	14.5
250–499	21	13.8
500–999	13	8.6
More than 1,000	73	48.0

Knowledge and Skills for Sensor Data Analytics

The open-ended questions in this section were intended to determine the knowledge-building areas of sensing technologies that workforce development should be focused on. The key sensing technologies, application areas, and insights were identified by conducting a qualitative analysis of the open-ended responses and clustering these inputs based on similar themes as shown in Table 4. This table provides a comprehensive list of information to assist in familiarizing with the essential knowledge areas of sensor data analytics.

The respondents were asked to select the skills they perceived as required to implement sensors and perform sensor data analytics. According to the frequency of responses, the chosen skills were ranked as shown in Figs. 2 and 3. The three most frequently cited skills for sensing technology implementation were problem identification, technological competency, and problem-solving. For sensor data analytics, problem-solving, modeling, communication, problem formulation, data processing and analysis, and collaboration were among the highest-rated skills. From Figs. 2 and 3, the frequencies of problem identification and problem-solving skills indicate that the respondents place significant emphasis on understanding the context for using sensing technologies and how to solve problems from sensor data. Open-ended responses were included under 'other skills' to capture additional skills beyond the

Table 4. Representation of key knowledge areas

Sensing technologies	Applications	Key insights
RFID	Access control; asset tracking; communication; equipment safety; resource management; underground structures detection and verification	Craft staffing levels; manhours worked; spatiotemporal status of resources; delivery and installation status of resources; cost
GPS	As-built verification; asset tracking; earthwork; equipment control; layout control; location detection; survey planning and control; productivity tracking; quality control	Installation quality; As-built conditions; layout accuracy; installation accuracy; resource status (e.g., material usage levels, installation, and location); earthwork volumes; resource usage levels
Laser Scanners	Bar code reading; BIM coordination; mapping existing conditions; inspection and verification; marking; quality control; surveys; progress tracking and monitoring	Conflicts in the field; project risks; installation accuracy; detection of defects; inconsistencies before concrete pour; resource quantity and status; roadway profiles and smoothness
Cameras	Ground and topo survey; visualization of site information; marketing; measurements of quantity/volume; progress tracking; project documentation; resource management; site monitoring and inspections; security; dispute resolution	As-built conditions; deviation; challenges; operations; Productivity; record-keeping or documentation support; safety and security; verification
GPR	As-built verification; concrete scanning; conflict identification; existing conditions survey; locate underground utilities; rebar detection	Location of obstructions, challenges to drilled shafts, and excavations; status of preexisting conditions; verification
Accelerometers	Deformation monitoring; vibration monitoring	Equipment performance; operational hazards; work permissibility
IMU	Concrete thermal control	Model accuracy and alignment
Others	Integration with virtual and augmented reality; COVID-19 screening measures; envelope inspections	Accuracy and quality; construction errors; COVID-19 regulatory measures; equipment status

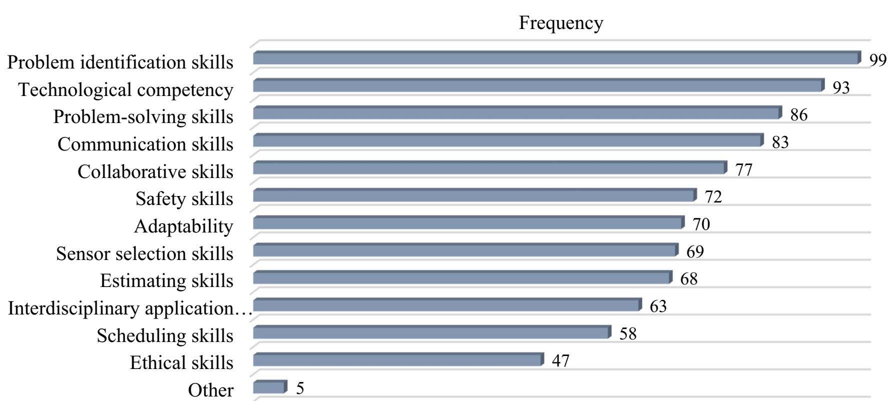

Fig. 2. Required skills for sensing technology implementation.

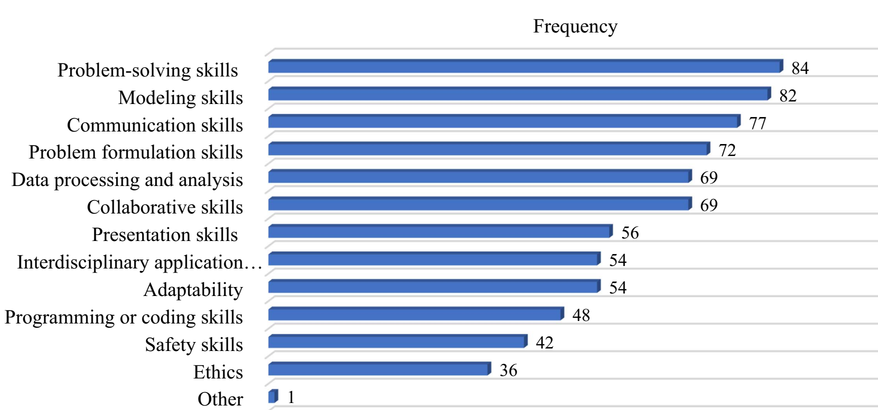

Fig. 3. Required skills for sensor data analytics.

Table 5. Perception of sensing technology implementation skills development

Skills	N	Mean	SD
Collaborative skills	74	3.89	0.79
Problem-solving skills	80	3.81	0.80
Problem identification skills	92	3.66	0.83
Adaptability	67	3.61	0.80
Communication skills	79	3.57	0.81
Technological competency	87	3.55	1.01
Interdisciplinary application skills	60	3.40	0.92
Ethical skills	44	3.34	0.86
Safety skills	67	3.34	0.93
Estimating skills	63	3.22	0.91
Scheduling skills	54	3.13	0.87
Sensor selection skills	65	3.03	0.98
Other	4	2.75	0.50

Table 6. Perception of sensor data analytics skills development

Skills	N	Mean	SD
Collaborative skills	66	3.71	0.84
Problem-solving skills	77	3.61	0.88
Communication skills	72	3.61	0.74
Modeling skills	77	3.53	0.91
Problem formulation skills	65	3.52	0.90
Adaptability	52	3.48	0.83
Presentation skills	54	3.48	0.79
Safety skills	38	3.42	0.89
Ethics	34	3.38	0.82
Data processing and analysis	64	3.25	0.84
Interdisciplinary application skills	49	3.24	0.85
Programming or coding skills	45	2.96	1.04
Other	1	5.00	0.00

predefined options. It was observed that some of these responses such as "communication," "BIM," "adaptability," "collaboration," and "ability to be technologically savvy" overlapped with skills already listed in the predefined options. Other skills reported were "interpretation" and "construction experience."

Extent of Skills Utilization among Construction Practitioners

The survey asked construction professionals if they use sensing technologies in their construction projects. The results revealed that a significant majority of construction professionals, comprising 85% of the participants, reported actively utilizing sensing technologies in their construction projects. The high percentage of affirmative responses underscores an increased uptake and integration of these technologies within the construction sector.

A 5-point Likert scale (Very Low = 1, Neutral = 3, Very High = 5) was used to gauge industry professionals' perceptions of the extent to which the skills are being developed to prepare CEM students. Tables 5 and 6 show the frequency, means, and standard deviations of survey respondents' evaluations of CEM students' academic preparedness. In both cases, the "Other" skills were shown at the end due to having a substantially small sample value. The skills perceived to be the least developed for implementing sensing technologies were sensor selection, scheduling, estimating, ethical, and safety skills. Similarly, sensor data analytics skills such as programming or coding, interdisciplinary application, data processing and analysis, and ethics were perceived to have the lowest academic preparedness.

The participants' responses to the extent to which the skills (i.e., sensing technology implementation and sensor data analytics) are important and were compared based on their experience in the construction industry and company size. For the levels of construction experience, only safety skills or ST6 for sensing technology implementation were found to have a statistically significant difference (i.e., $p < 0.05$) (see Figs. 4 and 5).

In terms of responses of the participants based on their company size, statistically significant differences (i.e., $p < 0.05$) were observed for only sensor selection or ST2 (for sensing technology implementation) and problem-solving (SDA5), and collaborative (SDA6) skills for sensor data analytics (see Figs. 6 and 7).

Practitioners were asked to indicate their companies' present practices regarding sensor data processing. Fig. 8 shows the contracting mode (i.e., in-house or outsourced) of sensor data analytics for each evaluated sensing technology.

Fig. 9 represents the length of time that professionals or companies have been processing construction-related sensor data acquired from the respective key sensing technologies. The findings for the investigated sensing technologies demonstrate that construction companies have increasingly been processing sensor data acquired from GPS, RFID, laser scanners, cameras, accelerometers, and others (e.g., robotic total stations, vibration monitors, concrete maturity meters) during the previous one to five years (see Fig. 9).

Value and Anticipated Demand

The majority of the participants (89.3%) indicated data analytics had a very high to medium influence on their project decisions.

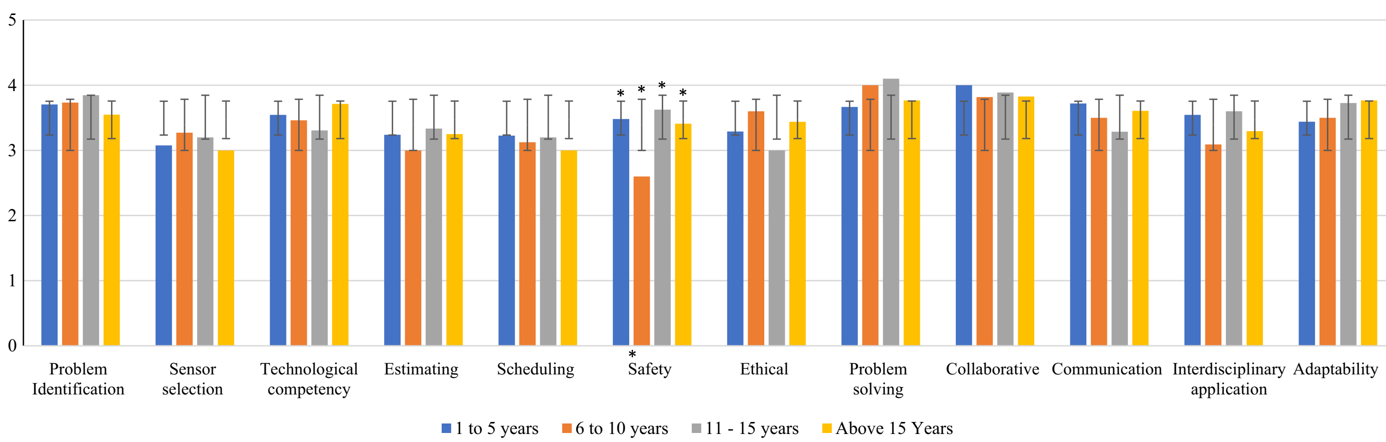

Fig. 4. Comparison of response averages between different groups (experience levels) for sensing technology implementation skills.

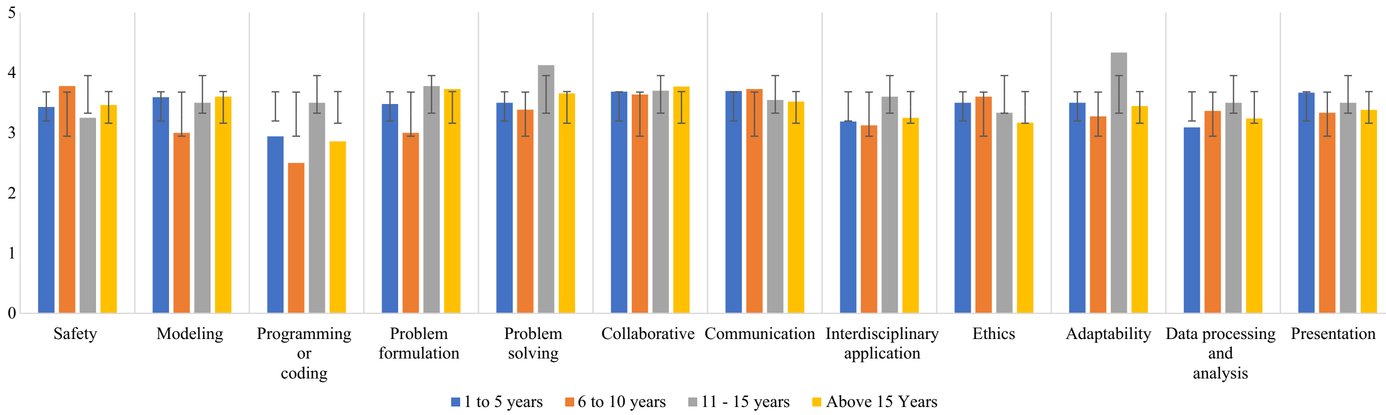

Fig. 5. Comparison of response averages between different groups (experience levels) for sensor data analytics skills.

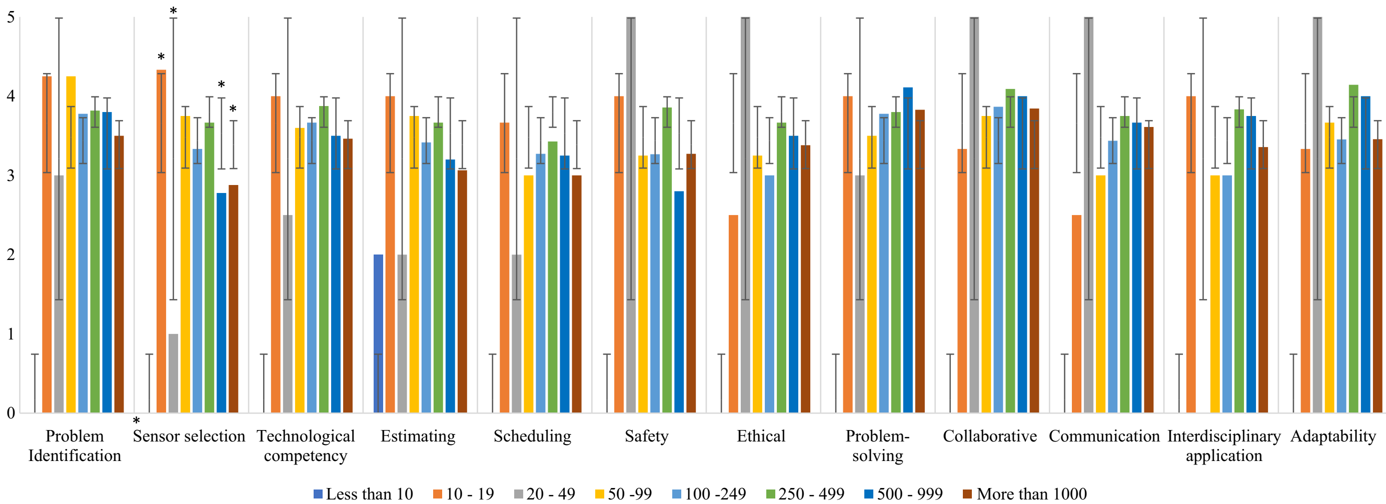

Fig. 6. Comparison of response averages between different groups (company size) for sensing technology implementation skills.

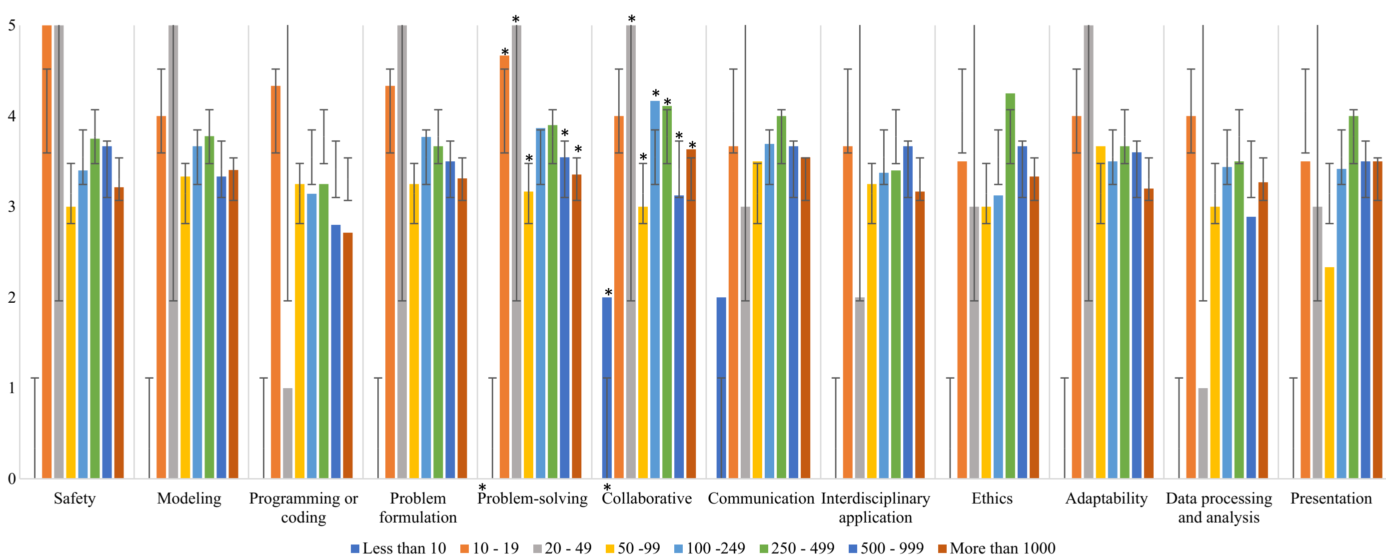

Fig. 7. Comparison of response averages between different groups (company size) for sensor data analytics skills.

Only 10.68% of the participants stated that the effect of data analytics was either low or extremely low (see Fig. 10).

In terms of adoption, 64% of the participating industry experts conceded that they were considering utilizing data acquisition or sensing technologies in the future, as shown in Fig. 11.

As shown in Fig. 12, Cameras (34%), GPS (25%), laser scanners (13%), GPR (13%), RFID (9%), IMU (3%), and others (3%) were chosen as the sensing technologies that professionals anticipate using in the future. No response was recorded for the anticipated usage of accelerometers.

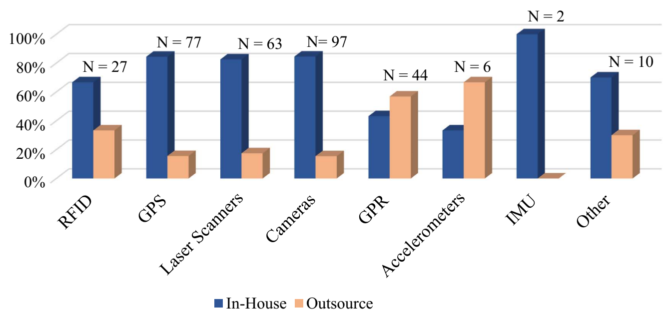

Fig. 8. Current status of contracting approach for sensor data processing.

Focus Group Validation

This section presents the findings from the qualitative analysis of the focus group transcript. Using the open-coding method of the transcript generated key themes across the comments of industry professionals (Saldaña 2009).

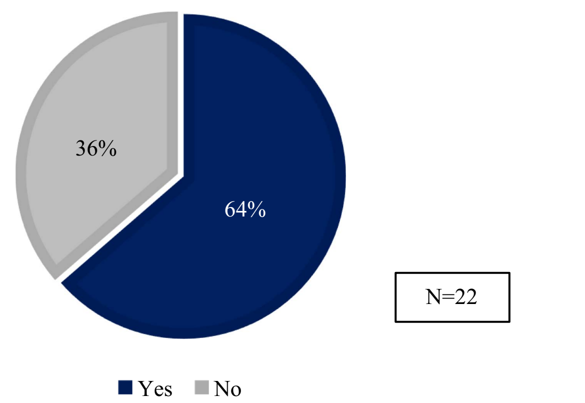

Fig. 11. Future adoption of sensing technologies.

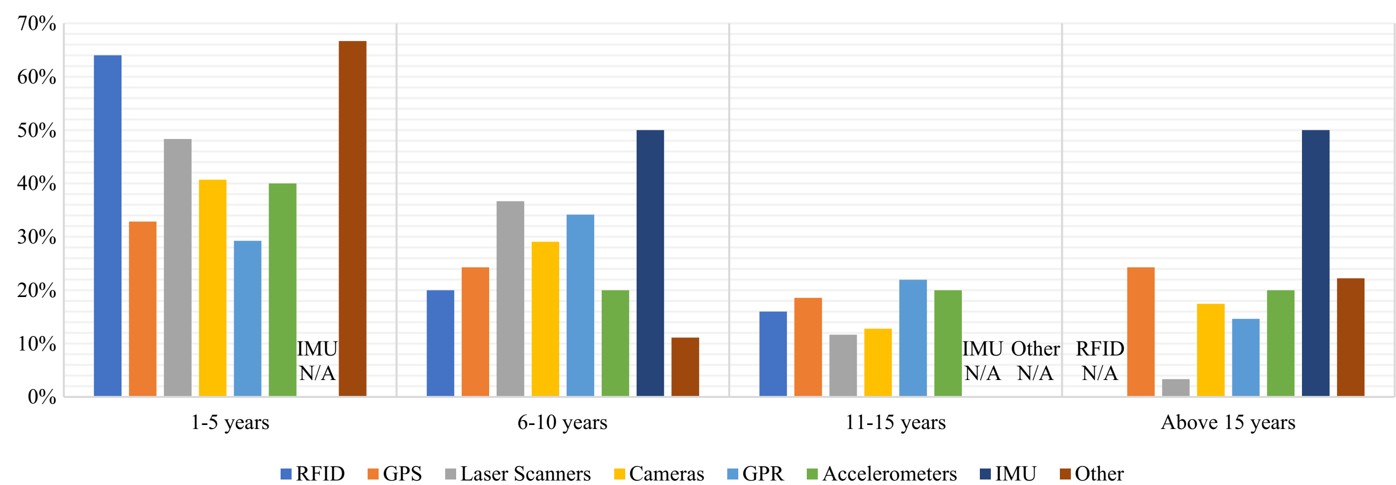

Fig. 9. Duration of performing sensor data analytics.

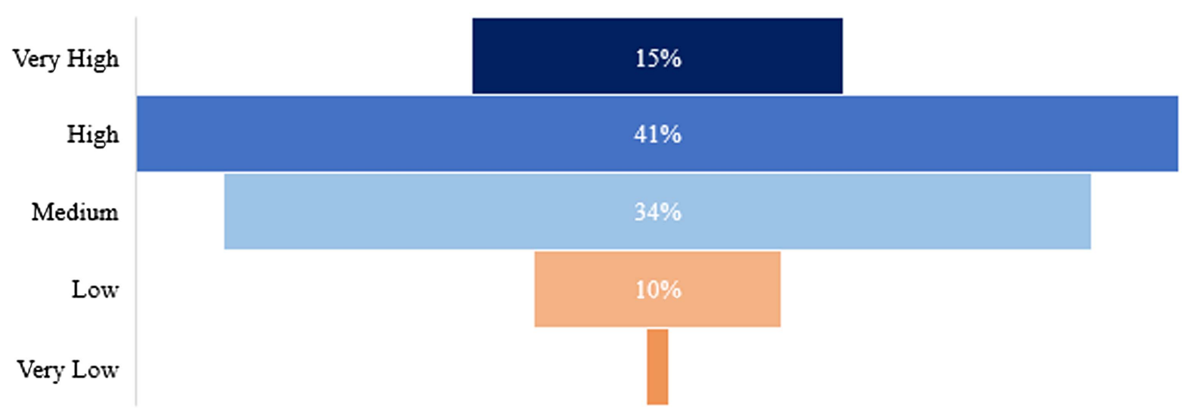

Fig. 10. Influence of data analytics on project decisions.

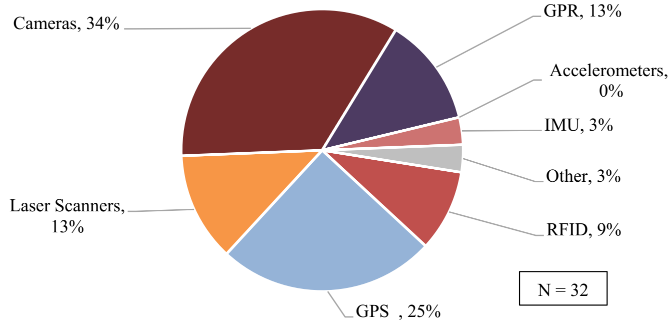

Fig. 12. Selected technologies for future adoption.

Knowledge and Skills Required for Sensor Data Analytics

The focus group participants were engaged in discussing the knowledge areas for sensor data analytics. The participants were provided with lists of the sensing technologies, applications, and insights identified from the previous section and were asked to provide feedback regarding its exhaustiveness in the context of the construction domain. Apart from the comprehensive list of major sensing technologies examined by the participants, they also mentioned additional technologies such as robotic total stations, terrestrial laser scanners, simultaneous localization and mapping (SLAM), noise monitors, NavVis units, cable pulling devices, water flow detectors, and atmospheric monitors. Similarly, all participants agreed that the lists comprised key construction applications and insights: "This covers a comprehensive list."; "It's a very good list."; "I think all these data types [from the key sensing technologies] can be certainly useful and relevant." One participant offered additional applications of sensors such as cameras: "Cameras are not only used for images and videos, but cameras ultimately generate point clouds for us." The significance of domain expertise was highlighted by a participant: "having a construction knowledge or the background is important as well."

The participants indicated their agreement with the sensing technology implementation skills, by the excerpts: "This list of skills is extremely important and beneficial;" "all of them, in my opinion, are important and extremely beneficial." Similarly, an agreement with the sensor data analytics skills was observed: "different individuals, depending on the end result they're looking for, which data they're processing, depending on the exercise, you know, they'll basically incorporate different, different skills I'm seeing."; "So, all those skills are all important and every person or the candidate needs to have in order to be successful."; "So, it's very important. I highly agree. It's very important to use for our field." Regarding the additional skills, one participant emphasized the social skill of adopting sensing technologies: "The social aspect of how this information is used, how these programs are communicated to the workforce are really important." Research skill was also stated in relation to selecting the appropriate technology for the given problem: "Research is also an important skill."

Perceived Importance of the Skills and the Extent of Utilization

The participants claimed that, in reality, employers look for candidates who can implement sensing technologies and analyze sensor data, demonstrating the importance of these skills. The consensus across all participants was that candidates were not necessarily tested but rather expected to possess certain extents of these skills if they had an academic degree in a construction-related discipline: "I think a lot of these skills are inherent in a rigorous four-year engineering degree, like you're not going to get through that curriculum without having some basic competency in most of these." The questions further revealed the contexts in which entry-level applicants can demonstrate their skills. Employers reportedly adopted a communicative approach to gauge applicants' exposure and understanding of the sensor data: "If they can demonstrate that they can understand the data and provide us insights from the data"; "We just talk about his experience and exposure to the data . . . will help us understand that they'll be able to achieve what we need."; "If the student can understand the data well, and if he can process the data and provide the insights of the data. So that is what we are looking for." Participants' responses demonstrate that construction sector employers placed high importance on finding skilled personnel to manage sensor data analytics in construction projects.

Value and Anticipated Demand

The construction experts indicated a significant influence of sensor data analytics and insights on construction project decisions: "I feel it is extremely important for us as a general contractor to . . . . know, as much information as possible about these projects, due to risk mitigation and controls. So, we, as a group, want to know everything. The technologies are great, but I feel you know, they definitely help us make better day-to-day decisions." Participants positively responded to the value and anticipated demand of sensor data analytics indicating the growing need for this knowledge and skills in future professionals: "So, we are looking for the candidates who can understand the data and provide us insights.'; 'this area is just growing, . . . the use of sensing data or advanced tools in construction . . . So right now, we are hiring people, training them on certain tools." Excerpts such as, "We're leaning toward other departments, trainings, and degrees to help augment our workflows to increase all that [sensor data analytics].'; 'I think construction is broadening the resource pool and grabbing other industries to be able to help construction." assert that employers are even expanding into other disciplines to find skilled individuals who can perform sensor data analytics in construction.

Challenges in Extracting Insights

The construction sector faces its own hurdles in matching with current technological advancements and a rapidly expanding knowledge base. The participants were asked to discuss the challenges they encounter while seeking actionable insights from sensor data and indicated the selection of appropriate sensing technology to be key in deriving the expected benefits: "And you just have to understand what your problem is, and make sure you're deploying the right one for that problem." Similar to this, the implementation of sensors on project sites necessitates in-depth knowledge of their functions and suitability to address the concerns of the workers (e.g., privacy concerns): "No one wants to wear an armband sensor or any sort of sensor on the body, because they don't want someone to watch every second. So how do we deal with it? And how do we first place identify what sensors we want to use to solve a problem?" Also, sufficient exposure to sensor data types was highlighted as necessary: "the more exposure they can get, the better whether it be means and methods, understanding general construction, and different technologies."

It was discovered that the challenge weighs heavily on the sensor data analytics workflow or process rather than the capability of merely collecting data through sensors, as participants noted: "what is the workflow, right, and sensors and tools to solve that problem?"; "it's more about the data silos that present the problem, not necessarily the tool."; "I think the ability to collect data is not that hard to make sense of it and be able to make better decisions is where the challenge is." The appropriate workflow of sensor data analytics can provide construction practitioners with actionable insights and facilitate informed decisions: "Yeah, we always say there is no one size fits all approach a lot of tools and tool built-in, and what's the end deliverable that every team is looking for." Also, participants noted the importance of accuracy and delivery time of sensor data analytics: "The biggest one [challenge] is the time, the commitment of analyzing the data."; "You're all right, not only accuracy, it's about the delivery time, too, if you're not getting the information shared at the right time, so they cannot make real-time decisions right."

Discussion

This research highlights the importance of incorporating sensor data analytics in construction engineering applications and educational programs. Through surveys and focus group validation, the findings offer evidence of the defined knowledge and skill sets, the extent of their utilization, and their value and anticipated demands. Results from the study suggest that knowledge of sensors, applications, and insights is important for practitioners to convert the results into formats suitable for effective decision making. This also supports the research by Arabshahi et al. (2022), suggesting that knowledge of sensing technologies is inextricably linked with potential benefits derived from the adoption and implementation. Therefore, it can be challenging for CEM students without the knowledge base of the applications of sensors (e.g., track progress, survey planning and control, and inspection) to comprehend how these generate various construction insights (e.g., project risks, conflicts in the field, resource quantity and status, and productivity) to facilitate decision making.

The 24 skills selected for this study were presented to the participants for their perspective on whether they were important to the application of sensors and data analytics. It was assumed that the participants reviewed and understood the lists of skills and their specific context in the construction as shown in Tables 1 and 2 [e.g., technological competency (i.e., ability to implement data acquisition/sensing technologies)]. Through descriptive statistics and thematic analysis, all the skills were found to have a positive perception of their need in the industry. For sensing technology implementation, problem identification was considered the most important skill that involves the identification of risks or challenges to be solved through sensor deployment. This skill was also highlighted by focus group participants in combination with sensor selection skill (8th ranked) and was acknowledged to be essential to deploying the appropriate sensing technology for the identified problem. Technological competency was perceived as the second most important skill that involves the ability to implement data acquisition or sensing technologies. The third most cited skill was problem-solving such as critical thinking and creative problem-solving, which was also highlighted by a focus group participant as "thinking outside the box" in terms of logical reasoning and making effective progress with sensor data-related applications. In addition to the top three cited skills, other skills were considered important through review and validation by focus group practitioners. For instance, the skill of scheduling ensures the deployment of the right sensors at the appropriate time and location for capturing relevant data, while the estimating skill enables the efficient allocation of necessary resources and cost-effectiveness of such solutions. Additional skills include recognizing the safety implications of these technologies, effective communication of clear ideas and concepts, and collaboration among project team members. Lastly, additional acknowledged skills encompassed the capacity to adapt to learning and managing risks, the incorporation of interdisciplinary thinking involving fields such as computer science, social science, and business management, as well as the integration of ethical considerations throughout the entire process.

For sensor data analytics, problem-solving was selected as the most important skill which involves the ability to describe or model a problem. Modeling was selected as the second highest important skill that involves abilities such as 2D and 3D drawing and building information modeling. The third highest rated was the communication skill involving the ability to verbally communicate ideas or solutions. The list also comprised skills in problem description and modeling, data processing and analysis, coding in key programming languages, and understanding the safety implications of sensor data solutions. In the realm of sensor data analytics, additional skills encompassed collaborative teamwork, interdisciplinary applications, adaptability, effective presentation, and ethical considerations pertaining to the handling of sensor data. Following the review of the skills list by the focus group participants, research and social skills were identified as supplementary capabilities. The findings are also supported by other research stating the development of expert skills is essential to utilize the functionalities of sensing technologies and sensor data (Ogunseiju et al. 2021b; Perisic et al. 2016).

The extent to which CEM students were perceived to be skilled appears to be related to the specific skills identified as necessary to address various construction issues. The skill types with high-frequency scores were regarded to be the ones that practitioners prioritized. In contrast, it was observed that skills such as sensor selection, scheduling, estimating, programming or coding, interdisciplinary application, and data processing and analysis were not selected as the most important in the survey results. Similarly, respondents' low appraisal of these specific skills underscores the academic backwardness through construction-related degrees. However, in-depth discussions with the professionals revealed that all the skills were considered essential to a certain extent that is dependent upon the nature of the construction problem. The comparisons of the respondents' perceptions based on their professional involvement, including their experience level and company size, indicated statistically significant differences between different groups. For the perception of safety skills, participants demonstrated statistically significant variations (i.e., $p < 0.05$). In comparison to both professionals with 1–5 years and with more than 10 years of experience, professionals with 6–10 years of experience demonstrated lower ($p < 0.05$) perceptions of safety skills, showing that individuals in this experience range perceive a greater inadequacy of academic preparedness in safety skills for implementing sensing technology.

Professionals' evaluations of skill developments (such as sensor selection, problem-solving, and collaborative skills) varied depending on the size of the firm, which might be explained by a further investigation into their organizational structure, capacity, technical expertise, and demands. First, participants working in companies with 10–19 employees perceived higher ($p < 0.05$) academic preparedness of sensor selection skills compared to participants in companies with 20–49, 500–999, and over 1,000 employees. On the other hand, participants (20–49 employees) perceived lower ($p < 0.05$) sensor selection skills compared to participants (50–99 and 250–499 employees). In terms of sensor data analytics, participants in companies with 10–19 employees perceived higher ($p < 0.05$) academic preparedness of problem-solving skills compared to participants (50–99, 500–999, and over 1,000 employees). Similarly, participants from companies with 20–49 employees showed a higher ($p < 0.05$) perception of problem-solving skill development compared to participants in companies with 50–99 employees. For collaborative skills, participants from companies with less than 10 employees have depicted a lower ($p < 0.05$) perception from participants (20–49, 100–249, and 250–499 employees). Alternatively, participants with 500–999 employees exhibited a lower ($p < 0.05$) perception of collaborative skill compared to companies with employee sizes ranging between 20–49, 100–249, and 250–499 employees. Additionally, participants from companies with 50–99 employees perceived a lower ($p < 0.05$) preparedness of collaborative skills compared to participants (20–49 and 100–249 employees). Conversely, participants with 100–249 employees showed a higher ($p < 0.05$) perception of collaborative skill development compared to participants from companies with 1,000+ employees.

The findings further show that the majority of the participating professionals have adopted sensing technologies in their projects. The sector in the past 1 to 5 years has been increasingly analyzing data from sensing technologies such as GPS, RFID, laser scanners, cameras, accelerometers, and others. Some of the reasons for outsourcing sensor data analytics to specialist contractors were identified to be the lack of "capacity to self perform," "skilled resources for data management," "software," "technical expertise," and "sophisticated training." One recurring theme was that in the absence of these resources, construction companies opted to outsource sensor data analytics since it was cost and time efficient when performed by specialists.

The study's results demonstrated that most industry professionals considered sensor data analytics to have a significant influence on the decision making process for construction projects that reinforces the value and future need for these skills and knowledge. Similarly, the most popular sensing technologies, including cameras, GPS, laser scanners, GPR, RFID, and IMU, exhibited evidence of current and potential adoption in the future. However, amid all the rapidly developing technologies, the final outcome that industry professionals want is the useful insights provided by these sensor data that can address certain construction issues. Participants in the industry claimed the workflow of sensor data analytics was more challenging than the ability to collect sensor data. As a result, the extraction of practical insights to guide construction decision making might become difficult (Liu et al. 2022). Despite the expectation for practitioners to possess essential technical skills and domain knowledge in the construction industry, the survey results reveal a trend where contractors are compelled to outsource their data analytics requirements regardless of possessing necessary construction knowledge (Perisic et al. 2016). Therefore, it can be inferred that the rising adoption of sensing technologies will continue to demand that CEM students be equipped with sensor data analytics skills and knowledge.

The survey consisted of a sample size of 152 participants. While this sample size may be adequate for perception research in the construction industry context, it may limit the attainment of strong representativeness and the generalizability of the findings. The survey data were analyzed to identify whether demographic characteristics such as company size and industry experience affected the industry perception of the required skills. Additional variables that could be considered include participants' educational or training backgrounds, levels of experience with particular sensing technologies, and the types of construction project involvement. This can provide additional contexts for targeting specific demographics for upskilling and inform future workforce planning by identifying sectors where individuals with these skills should focus their efforts for suitable employment opportunities. The thematic coding of the key applications and insights of the sensing technologies share certain interchangeable terms and were categorized to the best of the authors' knowledge while keeping in mind the practice of construction sensor data analytics. Further in-depth interviews would enable probing of the participants' responses and help to understand the insights sought from sensor data to facilitate decision making.

Conclusions and Future Work

In recent years, the applications of emerging sensing technologies have gained significant attention in construction with the aim to improve performance and increase productivity. However, research that investigates the knowledge and specific skills required for the workforce to effectively utilize these technologies is scarce. The authors observed that the survey and focus groups revealed a similar positive indication of how the research population perceived the need for this specific knowledge and skills. Therefore, this study acts as a base point for construction stakeholders focusing on the knowledge and skills required for sensor data analytics. Furthermore, this study presses that to enable the industry to thrive and derive the maximum benefits of sensor data analytics, CEM students who possess the domain knowledge of construction need to be equipped with the investigated knowledge and skills. This research concludes that all of the investigated skills are essential for CEM students, although the extent to which each skill is required varies depending on the business or construction problem it is geared to address. The findings can help educators and researchers determine the significance of each skill and priority when developing any sensor data analytics platforms or environments, whether for instruction or industry practice. Even beyond undergraduate education, the implication of the results can be applicable in community colleges. This conclusion lends further credence to the requirement for workforce development and practical application opportunities and should therefore be reinforced in professional development efforts. This research will help to launch systems that promote knowledge and skill mindfulness in educators and professionals, allowing them to be more effective in training the construction workforce.

As a progression of this research, the investigated knowledge and skills will be facilitated by developing programming environments to enhance experiential learning of sensor data analytics applications aimed at addressing authentic problems in the construction industry.

Data Availability Statement

All data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

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