Analysis of the Synergistic Effect of Data Analytics and Technology Trends in the AEC/FM Industry

Shahrzad Mansouri, A.M.ASCE[1]; Fadi Castronovo, Ph.D., A.M.ASCE[2]; and Reza Akhavian, Ph.D., A.M.ASCE[3]

Abstract: Technological advancements focusing on effective and efficient information modeling, visualization, resource tracking, and collaboration have gained substantial traction in the architectural, engineering, construction, and facility management (AEC/FM) industry in the last 10 years. The use of advanced technologies has resulted in safer jobsites hosting more productive project teams building more sustainable and resilient facilities and infrastructure. Recently, the innovative use of data and analytical approaches has had a major positive effect on a variety of businesses by incorporating data-driven applications and approaches. However, the AEC/FM industry is still lagging behind many other industries in leveraging the true power of data. Data analytics concepts and tools integrated with emerging construction trends such as building information modeling (BIM) have a high potential to revolutionize industry practices. This paper consolidates the record of current efforts in the AEC/FM body of knowledge (BOK) and body of practice (BOP) that incorporate the use of Data Analytics with common Technology Trends in various Application Areas. Identifying common subsections of each category, a three dimensional evidenced taxonomy was developed that maps (1) Data Analytics concepts such as cloud computing and machine learning onto, (2) AEC/FM emerging trends such as BIM and automation, and (3) existing and potential AEC/FM applications such as safety and progress monitoring. To further expand the validity of the results and explore opportunities and potential, a survey with the same categorization was developed and distributed among industry experts. Comparing the results of the exploration of the BOK and the survey illustrated the popularity of BIM among industry practitioners and in academic research. Also, process efficiency and productivity improvement were the two Application Areas that demonstrated the most potential to benefit from the integration of Data Analytics and Technology Trends. Analysis of the survey results indicated that, with a 95% confidence level, there is no statistically significant difference among the Technology Trends or Application Areas, as identified in the literature, that can benefit from Data Analytics. The results presented in this study demonstrate evidence of the revolutionizing power of Data Analytics in the AEC/FM industry. **DOI: 10.1061/(ASCE)CO.1943-7862.0001759.**

Introduction

Data has become the backbone of decision-making processes in almost all industries. The revolutionizing power of insights offered through Data Analytics has affected the architectural, engineering, construction, and facility management (AEC/FM) industry as well. While the AEC/FM industry has been historically slow to adopt new ways and advanced approaches, it is now moving at a faster pace to leverage the power of data through technology adoption. In a recent report entitled *The New Age of Engineering and Construction Technology*, McKinsey and Company indicated that "Many of the best construction-technology tools incorporate data from both past and ongoing projects into their decision-making algorithms" (Blanco et al. 2017). A considerable positive impact on decisions made at the corporate, program, and project levels is achieved through data-informed knowledge generation. As a result, supplementing the Technology Trends and concepts that are being established as industry standards, such as building information modeling (BIM), with data can result in substantial process improvements in project execution. According to a recent report by McKinsey and Company, although project sites now generate a vast amount of data that is rarely captured, the use of Technology Trends and digitalization enable firms to improve efficiency, timelines, and risk management through data collection and analytics (Agarwal et al. 2016). The use of technology and data-driven applications, however, is not consistent among industry players. The biggest gap can be seen between engineering and construction companies and owners; engineering and construction companies are ahead of owners in adopting technology (Armstrong and Gilge 2016).

The objective of this research study was to explore the synergistic potential of and future opportunities for existing Technology Trends to be integrated with Data Analytics concepts. Considering the inconsistency of the adoption of technology in construction, the contribution of this study lies in its attempt to discover both existing implementations and future potential for major players in construction projects. Toward this goal, recent efforts in both the academic community and industry were scrutinized in this research. During the last few decades, researchers have studied new Technology Trends (Golparvar-Fard et al. 2009; Bosche and Haas 2008; Song et al. 2006; Akhavian and Behzadan 2018). A comparison of the academic and industry communities illustrates the need for a spark of motivation for industry to incorporate the use of Data Analytics in order to realize more of the benefits of implementing Technology Trends. Such trends include BIM, virtual and augmented reality (VR/AR),

[1]Graduate Student, School of Engineering, California State Univ., East Bay, Hayward, CA 94542. Email: smansouri@horizon.csueastbay.edu

[2]Assistant Professor, School of Engineering, California State Univ., East Bay, Hayward, CA 94542. Email: fadi.castronovo@csueastbay.edu

[3]Assistant Professor, Dept. of Civil, Construction, and Environmental Engineering, San Diego State Univ., San Diego, CA 92182 (corresponding author). ORCID: https://orcid.org/0000-0001-9691-8016. Email: rakhavian@sdsu.edu

Note. This manuscript was submitted on September 27, 2018; approved on July 3, 2019; published online on December 23, 2019. Discussion period open until May 23, 2020; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Construction Engineering and Management***, © ASCE, ISSN 0733-9364.

simulation modeling, and robotics and automation (Golparvar-Fard et al. 2011; Feng et al. 2013; Akhavian and Behzadan 2015a; Castronovo et al. 2013; Mastrolembo Ventura and Castronovo 2018) with applications in different areas, such as safety or productivity improvement (Wood 2016; Marr 2016). Recent research has indicated that although Data Analytics is gaining traction in the construction industry, its applicability could be truly recognized and amplified through emerging trends such as BIM, cloud computing, smart buildings, and augmented reality (Bilal et al. 2016b). While studying such integrations sheds light on areas with an abundance or a lack of research in the academic research community, it also helps practitioners identify existing promising technological frameworks and potential future approaches to benefitting from data-integrated technologies.

In this research study, a taxonomy of published studies that uses Data Analytics concepts along with Technology Trends for specific Application Areas in construction was developed. The depth of the review and the breadth of the range of different publications included in this study make it a valuable knowledge base for future research in these areas. In addition, a survey was developed and distributed among industry practitioners in order to gauge their opinions regarding the synergy between Technology Trends and Application Areas. Finally, the results obtained from the academic literature exploration and the industry expert opinions were quantitatively analyzed in order to compare and contrast the insights from these two schools of thought.

Methodology

The academic and industry communities in the AEC/FM field are known to be segregated in their views and in the level of adoption of Data Analytics and technology (Leite et al. 2016; Blanco et al. 2017). As a result, in this study these two groups were evaluated by separate tools, although similar measures were used to perform the evaluation. This allowed a systematic assessment of whether and to what extent such a gap exists. The first tool was a systematic literature exploration, which was used to investigate publications that focus on the use of predetermined Data Analytics concepts in conjunction with a set of specific Technology Trends in particular Application Areas. The three identified sets of (1) Data Analytics, (2) Technology Trends, and (3) Application Areas were then used to design a second tool, a questionnaire for survey research, given to construction experts.

In this section, the literature exploration process is described and the results are presented. Next, the industry survey design and methodology are presented, along with the survey results. The two phases of this research, that is, the literature exploration and the industry survey, were independent in nature. A preliminary literature review revealed many AEC/FM areas of high demand in terms of Technology Trends that can leverage Data Analytics to benefit specific Application Areas. These identified concepts were then used in the two phases. Highlights of the first phase were then compared to the second phase in order to explore the extent of the gaps and similarities.

Literature Exploration

In the first step of the methodology, three dimensions, which consisted of Data Analytics, Technology Trends, and Application Areas, were defined, and a set of related concepts was identified in each dimension. The first dimension includes prevalent Data Analytics concepts such as big data, predictive models, and clustering algorithms. In determining the components of the Data Analytics dimension, the significance and prevalence of the factors in other research domains such as computer science were considered as well. Likewise, components currently being investigated in the industry were also included (Wood 2016; Marr 2016). For the second dimension, Technology Trends, concepts were identified that have the potential to be integrated effectively with Data Analytics. Finally, the last dimension, Application Areas, represents the areas with the most potential to be affected by the integration of Data Analytics and Technology Trends, according to recent research studies (Armstrong and Gilge 2016; Agarwal et al. 2016; Blanco et al. 2017). Fig. 1 shows the components of each dimension that were used and mapped onto each other in order to discover the research studies in their intersections.

In developing these dimensions and the associated components, an attempt was made to maintain a level of detail that was neither too fine-grained nor too coarse. For example, machine learning is a component that encompasses predictive models, regression models, classification models, and clustering algorithms. However, predictive models, for example, are not necessarily based on machine learning concepts (Friedman et al. 2001). The Technology Trends and Application Areas chosen were those that have most frequently been integrated with Data Analytics concepts, per an initial literature screening. For example, three-dimensional (3D) printing is indeed a technology trend, but it is not included, because, to the best of the authors' knowledge, it has not been frequently integrated with Data Analytics concepts in the existing literature. In addition, data management is a concept that could have been included under Data Analytics, but it was considered as part of the data analysis component. ASCE's technical council on computing and information technology (TCCIT) and its data sensing and analytics (DSA) and visualization, information modeling, and simulation (VIMS) committees have also identified all these Technology Trends among those affecting grand challenges in the AEC/FM industry (Golparvar-Fard et al. 2013, Leite et al. 2016).

A large number of published research studies related to the defined dimensions were explored by means of a comprehensive keyword search of specialized journals and conference proceedings, such as the ASCE *Journal of Computing in Civil Engineering* and the Elsevier Science *Journal of Automation in Construction*, as well as search engines, such as Google Scholar and Engineering Village. To find more relevant papers, once an article was selected, the bibliography of the article was also scanned. This significantly increased the number of papers investigated and enriched the database.

Delimitation of the Literature Exploration

The process of literature exploration in this research involved only publications that included the identified Data Analytics, Technology Trends, and Application Areas, and all the papers identified were published between the years 2001 and 2018. Ample research was found that focuses on one of the aforementioned categories; for instance, Bradley et al. (2016) discusses some aspects of BIM as a technology trend but does not contain any information pertaining to

Data Analytics	Technology Trends	Application Areas
a. Big Data	1. BIM	1. Safety
b. Data Mining	2. Automation	2. Productivity
c. Data Analysis	3. AR & VR	3. Sustainability
d. Predictive Models	4. Simulation Modeling	4. Process Efficiency
e. Regression Models	5. Laser Scanning	5. BLM
f. Classification Models	6. Sensing & Monitoring	6. Lean Construction
g. Clustering Algorithms		7. Progress Monitoring
h. Cloud Computing		

Fig. 1. Components of the three dimensions defined for the taxonomy.

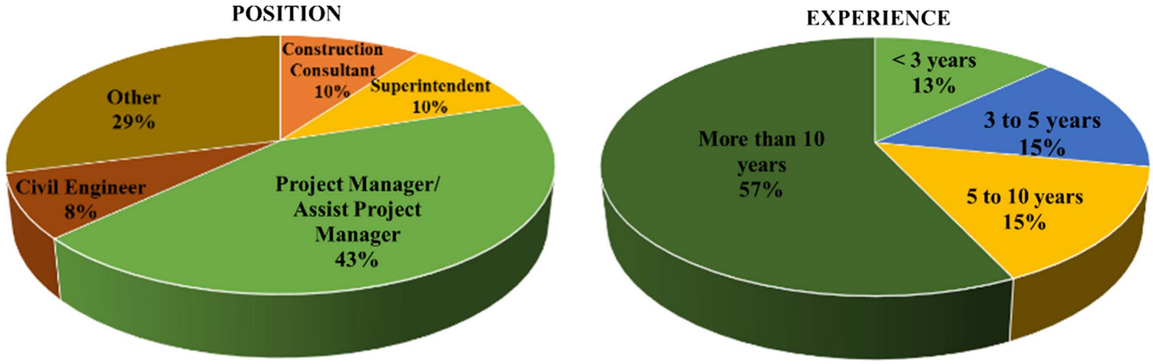

Fig. 2. Participants' positions and construction experience.

the other two dimensions, Application Areas and Data Analytics. Another example is a publication is that only focuses on safety, which was one of the identified Application Areas, but does not include the implementation of Data Analytics and Technology Trends as part of the research (Fang et al. 2006).

Industry Survey

The survey was designed using Google Forms as the questionnaire tool and was sent out to more than one hundred industry experts in the United States. The target industry experts were chosen from construction companies with a track record of incorporating advanced technology in their projects. The questionnaire consisted of seven questions and was expected to take no more than 10 min to complete. At the beginning of the questionnaire, a definition was provided to ensure the consistency of participants' understanding and reduce potential bias: "Data Analytics in this study, refers to examining raw data collected from or for construction projects to develop data-driven insight, make decisions, or draw conclusions for planning, execution, management, and control." The first two questions sought information about the participants' current positions and industry experience in order to explore their profiles. The third question inquired about participants' experience with Technology Trends. Questions 4 and 5 presented Likert scale choices for participants to express their level of agreement regarding the effectiveness of Data Analytics concepts when integrated with Technology Trends and the Application Areas identified in the academic literature search, respectively. The Likert scale choices were assigned numeric values as follows: strongly disagree = 1; disagree = 2; neither agree nor disagree = 3; agree = 4; and strongly agree = 5. Question 6 collected ordinal data about existing barriers that prevent the widespread adaption of Data Analytics. In other words, the goal of this question was to identify obstacles that prevent Data Analytics from being used in the construction industry to its full potential, as it is being used in various other industries. The last question was an open-ended question that provided an opportunity for participants to add their comments and provide us with their feedback.

Participant Profiles

Out of the more than 100 industry experts invited to participate, 55 responded to the survey. The survey was distributed to construction companies that are known for their tendency to adopt advanced technologies in their projects. Because the survey was distributed to employees of these companies, the number of people who received the survey is not precisely known. No data was collected regarding the location of the participants, but all the invitees were from the United States. Data on the participants' backgrounds and their experience with technology are presented in Figs. 2 and 3, based on responses to the first three questions. As shown in Fig. 2, more than 40% of the participants were project managers or assistant project managers. Also, 57% of them had 10 or more years of experience in the construction industry. According to Fig. 3, the participants' responses to the question about their experience with Technology Trends showed that BIM has the highest degree of implementation at 52%, while simulation modeling and AR/VR, at only 11%, had been rarely deployed among this sample. Responses to the technical questions about the integration of Data Analytics concepts and Technology Trends are presented in the next section.

Results

Literature Exploration Results

A taxonomy consisting of components in the three dimensions of Data Analytics, Technology Trends, and Application Areas was designed and presented as a coded grid in order to classify the identified papers and present the results of the literature exploration. The designed taxonomy is shown in Fig. 4. The Technology Trends and Application Areas were assigned to the horizontal and vertical axes of the grid, respectively. The horizontal axis was marked with numbers from 1 to 6 and the vertical axis was marked with number from 1 to 7; the numbers were associated with the components of the dimensions as shown in Fig. 1. For instance, a "1" on the horizontal axis, refers to BIM from the Technology Trends components, and a "1" on the vertical axis refers to safety from the Application Areas components. The Data Analytics components

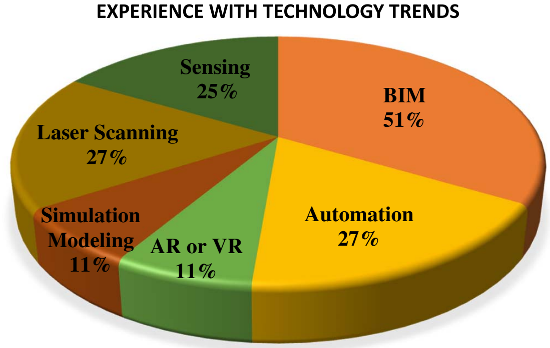

Fig. 3. Participants' technology experience.

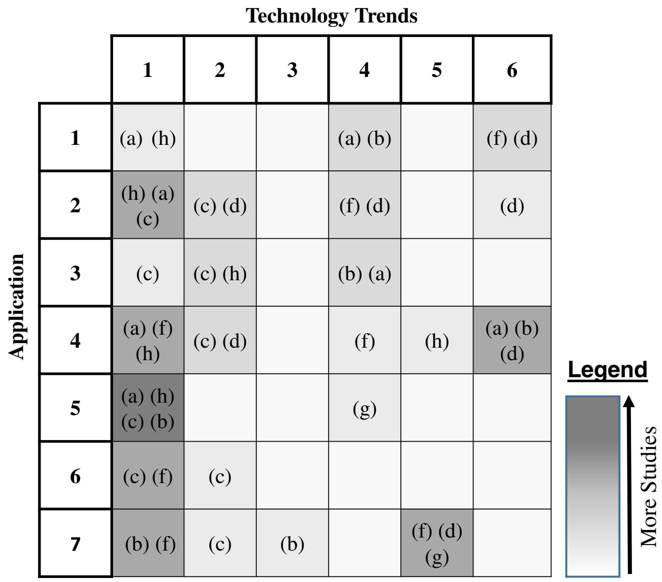

Fig. 4. Taxonomy of the study of the three dimensions.

were assigned to each cell using letters as shown in Fig. 1. For instance, the letter "a" refers to big data from the Data Analytics components. The shading indicates the level of implementation of Data Analytics with Technology Trends to solve problems in the different Application Areas. The darker a cell is, the higher the frequency of studies on that particular conjunction of the three dimensions. In this coded grid, certain categories can be extracted by their alphanumeric codes. The first character of each code is the letter corresponding to the Data Analytics component in Fig. 1. The two other characters are the numbers corresponding to the Technology Trends and Application Areas in Fig. 1. For instance, a-1-1 refers to a study that uses big data and BIM for project safety. All publications and category codes are shown in Table 1. Therefore, this taxonomy summarizes the current state of knowledge in the AEC/FM industry regarding the combination of Data Analytics and Technology Trends for specific Application Areas and shows the amount of research identified in each area.

According to the taxonomy shown in Fig. 4, within the dimension of Technology Trends, the BIM category has the highest potential for integration with Data Analytics concepts. In the dimension of Application Areas, process efficiency has benefited the most from Data Analytics techniques, especially when combined with BIM or sensing and monitoring.

Table 1. Category codes for the developed taxonomy and the corresponding publications

Category	Citation
a-1-1	Han et al. (2012)
a-1-2	Mao et al. (2007) and Jiao et al. (2013)
a-1-4	Bilal et al. (2016a)
a-1-5	Jiao et al. (2014)
a-1-5	Lin et al. (2016)
a-4-1	Akhavian and Behzadan (2015b)
a-4-3	Sanyal and New (2013)
a-6-4	Bilal et al. (2016a)
b-1-5	Dávila Delgado et al. (2015)
b-1-7	Turkan et al. (2012)
b-3-7	Golparvar-Fard et al. (2009)
b-4-1	Liao and Perng (2008)
b-4-3	Akhavian and Behzadan (2014)
b-6-4	Soibelman et al. (2004)
c-1-2	Jardim-Goncalves and Grilo (2010) and Grilo and Jardim-Goncalves (2010)
c-1-3	Akbarnezhad et al. (2014)
c-2-3	Tabachnick and Fidell (2007)
c-1-5	Akbarnezhad et al. (2014) and Bryde et al. (2013)
c-1-6	Arayici et al. (2011)
c-2-2	Zhai et al. (2009)
c-2-4	Cheung et al. (2012)
c-2-6	Arayici et al. (2011)
c-2-7	Han and Golparvar-Fard (2015) and Golparvar-Fard et al. (2011)
c-4-3	Akhavian and Behzadan (2013)
c-5-7	Bosché (2010)
c-5-8	Tang et al. (2011) and Zhang et al. (2016)
d-2-2	Kim and Soibelman (2002)
d-2-4	Feng et al. (2013)
d-4-2	Akhavian and Behzadan (2016)
d-5-7	Shen et al. (2013)
d-6-1	Han et al. (2012)
d-6-2	Akhavian and Behzadan (2016)
d-6-4	Akhavian and Behzadan (2016)
f-1-4	Liu et al. (2016)
f-1-6	Ahn et al. (2012)
f-1-7	Dimitrov and Golparvar (2014)
f-4-2	Akhavian and Behzadan (2015a)
f-4-4	Mahfouz (2009)
f-5-7	Turkan et al. (2012)
f-6-1	Gonsalves and Teizer (2009)
g-4-5	Chang and Tsai (2013)
g-5-7	Zhang et al. (2016) and Chai et al. (2016)
h-1-1	Park et al. (2016)
h-1-2	Grilo and Jardim-Goncalves (2011)
h-1-4	Redmond et al. (2012)
h-1-5	Jiao et al. (2013)
h-2-3	Rawai et al. (2013)
h-5-4	El-Omari and Moselhi (2008)

Survey Results

When asked about their level of agreement with the effectiveness potential of integrating the identified Technology Trends with Data Analytics concepts, the majority of the survey participants agreed or strongly agreed regarding BIM, which scored 4.02 out of 5 based on the Likert scale values described previously. AR/VR had the lowest score, 3.55 out of 5. The participants were also asked about Application Areas that could be positively affected by the integration of Technology Trends with Data Analytics concepts. In this case, the majority agreed or strongly agreed that productivity could be the most positively affected application area as a result of such integration among the areas identified, with a score of 4.26 out of 5. The answers to this question indicated that building lifecycle management (BLM) has the lowest potential to be positively affected by such integration, with a score of 3.81 out of 5. Figs. 5 and 6 show the scores and standard deviations for all six Technology Trends and seven Application Areas identified.

In response to Question 6 on barriers to the widespread adoption of Data Analytics in construction, the majority of the participants selected the "Lack of Training for the Personnel" as their first or second choice. "Technology-Averse Practitioners" was another important barrier from the participants' standpoint, while "Lack of the Need for It" was the least important barrier. Fig. 7 presents the results for this question. The horizontal axis shows the rankings of the barriers and the vertical axis indicates the percentage of the responses associated with the ranking.

The last question—the open-ended question—included some valuable information. One response stated: "I believe using newer

J. Constr. Eng. Manage., 2020, 146(3): 04019113

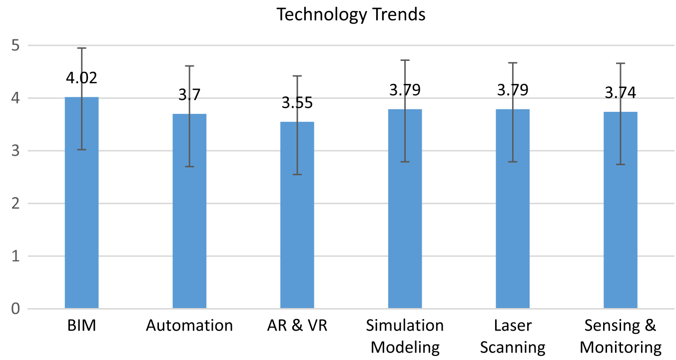

Fig. 5. Technology trends scores based on participants' responses (Question 4).

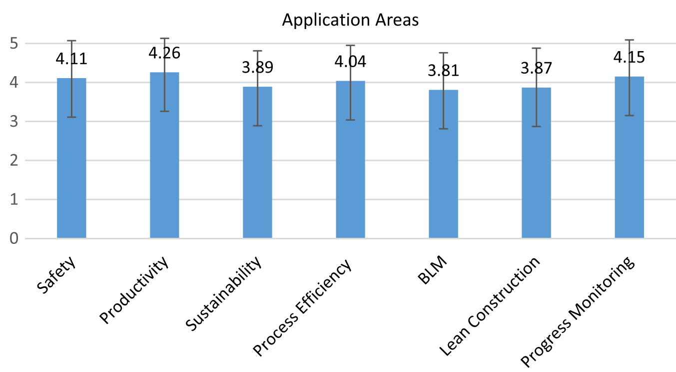

Fig. 6. Application areas scores based on participants' responses (Question 5).

technology will enhance construction [processes] and Data Analytics will make it more precise." Another response stated: "In retrospection of the integration of 'Data Analytics,' it must rest on the sophistication of the person or team in charge of the project. Moreover, the investment growth of the project and the coordination with other current or near future infrastructure surrounding the project are paramount to its implementation." A concern was mentioned in another response, which stated: "These technologies can undoubtedly make the industry more efficient and it is difficult to do this without Data Analytics but it threatens to displace and affect many individuals in the industry and their job security."

Comparative Analysis

Responses to Questions 4 and 5 addressed the level of effectiveness of the integration of Technology Trends and Data Analytics concepts and the most positively affected Application Areas. In order to compare the results obtained from the literature exploration to these responses, a two-step verification and validation statistical analysis was performed. The verification step leveraged the powerful one-way analysis of variance to test the responses received in the industry survey with regard to the assumptions made in the literature exploration. ANOVA tests the null hypothesis that the means of different groups are all equal and determines the possibility of the random error effect (Kao and Green 2008). If the average between the score of different Technology Trends (Application Areas) relative to the average within the individual Technology Trends (Application Areas) was high, the F statistics would go up. In this case, there would be a higher chance of rejecting the null hypothesis. The F statistics obtained were compared to the critical value using the available F tables in statistics textbooks in order to reject the null hypothesis if the F-test statistics $> F^{CV}$ (critical value).

In the validation step, the results of the literature exploration were assessed through a standard Student's t test. In this process, pairwise t tests were performed between the highest ranked technology trend/application area component in the literature exploration and all the other components in the group. This step was to evaluate whether the technology trend/application area component that had the highest promise for effective integration/results was statistically significantly higher than all the other components in its group from the industry experts' standpoint. In the first phase of this research and as a conclusion of the literature exploration, BIM was selected as the most promising technology trend for effective integration with Data Analytics. Therefore, the research team selected BIM and compared it with all other Technology Trends in a pairwise fashion. The same procedure was followed for process improvement as the application area that had the most potential to be positively affected by this alliance. In this study, the term BIM refers to the "modeling technology and associated set of processes to produce, communicate, and analyze building models," as described by Eastman et al. (2011).

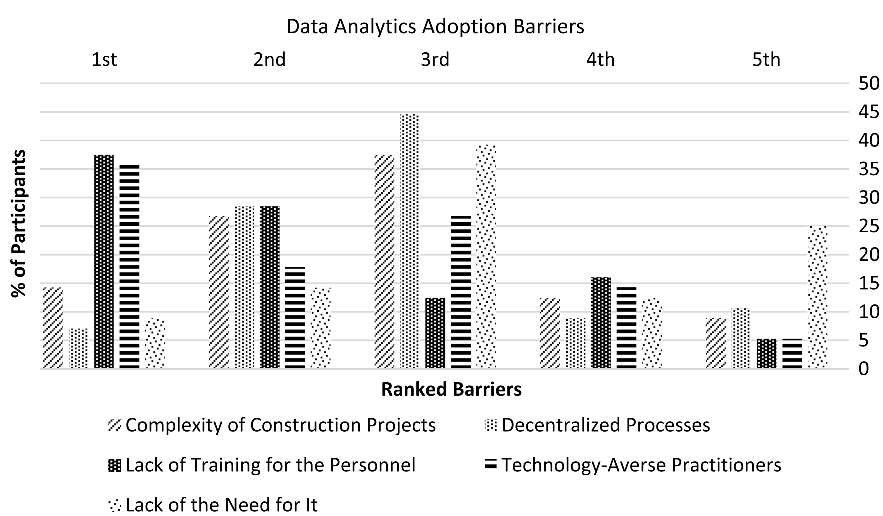

Fig. 7. Barrier rankings versus the percentage of participants ranking the barrier (Question 6).

Table 2. Pairwise Student's t test summary for BIM versus other Technology Trends

Technology trends	Automation	AR/VR	Simulation	Laser scan	Sensing
t statistics	1.79	2.70	1.26	1.28	1.57
Null hypothesis	Not rejected	Rejected	Not rejected	Not rejected	Not rejected

For the ANOVA, the null hypothesis was set as H_0: all population means are equal. With a 95% confidence interval ($\alpha = 0.05$), the hypothesis was tested and the results were as follows. For Technology Trends, $F = 1.53$ and $F^{CV} = 2.24$; therefore, the decision was to not reject the null hypothesis. For Application Areas, $F = 1.67$ and $F^{CV} = 2.12$; therefore, the decision was to not reject the null hypothesis. The results of the Student's t test are shown in Tables 2 and 3. The null hypothesis here was H_0: the two means are equal. The confidence level was 95% ($\alpha = 0.05$). The t critical value was 1.98 for both Technology Trends and for Application Areas.

Discussion of Results

This section presents the insights obtained from the different portions of the analysis in this study. First, the results of the research literature exploration are discussed. Next, the results of the survey are discussed, followed by a discussion of the comparative analysis that was performed. Furthermore, recommendations for research, potential for implementation, and potential barriers are provided in each subsection.

Literature Exploration

A lack of research and an abundance of opportunities in some areas can be clearly observed by reviewing the developed taxonomy, shown in Fig. 4. BIM (No. 2 under Technology Trends) showed the highest potential among the Technology Trends for integration with Data Analytics concepts in all Application Areas. This was expected because of the relative maturity of BIM-related research, which includes a wide variety of concepts, processes, and tools, including 3D modeling and four-dimensional (4D) simulation, constructability analysis and clash detection, and related software packages and respective add-ons. Productivity (No. 2 in Application Areas), process efficiency (No. 4 in Application Areas), and BLM (No. 5 in Application Areas) were the highlights of the taxonomy among the Application Areas that could benefit from such integration. Automation and simulation modeling are the runner-up Technology Trends in the taxonomy and their popularity can be attributed to the broad range of concepts that can be associated with their definitions. However, very few existing research studies have attempted using AR/VR with Data Analytics concepts in order to achieve better results. This can be justified by the fact that, in order for applications of AR/VR to be integrated with and benefit from advanced Data Analytics concepts, computer vision could serve as a viable approach; however, incorporation of AR/VR with computer vision and Data Analytics concepts is still a subject of ongoing research in computer science and related engineering fields (Alhaija et al. 2018). This is an important area of research that can be leveraged, considering recent advancements in visualization frameworks. This finding reveals the demand for research studies that leverage visualization techniques through an integrated framework of AR/VR and Data Analytics.

From the Application Areas standpoint, process efficiency had the highest number of publications overall that focused on using Data Analytics concepts with Technology Trends. Efficiency is an area of research that has made considerable positive impacts on other fields, such as health care (Bates et al. 2014), management sciences (Marr 2015), and finance (Cao et al. 2015). As a result, it is not surprising that such a trend exists in AEC/FM research, seeking to help improve efficiency. Reducing inefficiency through lean principles was separately studied in this literature exploration; this topic was much less apparent in the existing literature. There is still a huge potential for transforming traditional methods of applying lean construction methods, such as pull planning, using Data Analytics.

Survey Results

The results obtained from the survey demonstrated that the majority of the respondents, representing the industry in this research, endorse the capabilities of Data Analytics concepts in combination with the Technology Trends in all the identified Application Areas. However, the weight given to BIM was higher than that given to all the other areas, as was the case in the literature exploration. While this can be attributed to the major implementation of BIM concepts in the industry, it is worth mentioning that AR/VR, which is usually used to visualize information models, does not have the same popularity, according to this survey. This similarity—the popularity of BIM versus the lower potential of AR/VR as seen in both the responses of the industry experts as well as in the research community—is an interesting finding of this study.

As far the Application Areas are concerned, from the industry professionals' standpoint, productivity has more potential to be enhanced through data-enabled technology than all the other identified areas. While productivity does not have a single definition in construction, the industry is univocal in the fact that productivity requires a boost and that this study shows that it is possible through technology that is enhanced by data. This is in line with recent reports published by major management consulting firms in the US regarding the construction industry (Armstrong and Gilge 2016; Agarwal et al. 2016; Blanco et al. 2017). BLM, however, shows the lowest potential to be affected by the alliance of data and technology, according to the participants in this survey. This, to a large extent, could be the result of a lack of technology-enabled applications for facility management (Pärn et al. 2017).

In terms of barriers to the adoption of Data Analytics, the AEC/FM literature was in line with the results obtained from the survey. For instance, Eadie et al. (2013) indicated that the cost of implementing BIM is one of the barriers to a widespread technology adoption in the industry. The survey results for Question 6 also revealed that the majority of the respondents ranked "Lack of Training for the Personnel" first among the barriers. This was followed

Table 3. Pairwise Student's t test summary for process improvement versus other Application Areas

Application areas	Safety	Productivity	Sustainability	BLM	Lean	Progress monitoring
t statistics	0.41	1.29	0.83	1.24	0.90	0.62
Null hypothesis	Not rejected	Not rejected	Not rejected	Not rejected	Not rejected	Not rejected

by "Technology-Averse Practitioners," which has been previously identified as a barrier in the literature.

Comparative Analysis Results

The purpose of this analysis was twofold. First, ANOVA was used to see if there was any significant difference between the Technology Trends and Application Areas identified in the survey, taken from the participants' viewpoints, for Questions 4 and 5. Second, a Student's *t* test was used to compare BIM to all other Technology Trends and to compare process efficiency to all other Application Areas. This was because these two components appeared most often in the literature, according to the taxonomy shown in Fig. 4.

The ANOVA test revealed that no statistically significant difference existed among the Technology Trends identified in the literature with regard to their effectiveness in integration with Data Analytics concepts, based on the industry survey responses. A similar trend was observed in the results of the ANOVA test on the industry survey responses for Application Areas. This confirmed the veracity of the choices extracted from the literature. It also indicated that the research community and industry professionals have similar evaluations of the effectiveness of the integration of data-driven decision-making strategies for different applications in the industry. This may also be an indication of academic support and industry willingness to implement Data Analytics with Technology Trends in the industry.

In the pairwise Student's *t* test, BIM did not show any significant difference when compared with the other Technology Trends except for AR/VR. BIM had the highest score in the industry survey in addition to being the most implemented component according to the taxonomy of the literature exploration results. This result is particularly interesting, because it is another confirmation that, relative to a trend such as BIM, AR/VR has not shown as much potential for success in integrated data-enabled or data-driven frameworks. This is in line with the results obtained in the literature exploration. Among the Application Areas, the process improvement score showed no significant difference relative to the other components when compared pairwise, which is another reason to believe that all the identified areas have high potential for disruption as a result of technology–data integration.

Conclusions and Future Directions

In this research study, Data Analytics concepts, Technology Trends, and Application Areas were the three main areas of focus in reviewing the existing literature and conducting an industry survey within the AEC/FM community. The detailed analysis provides a simple yet comprehensive knowledge base for pinpointing relevant research studies in the prevalent Data Analytics areas that use trending technologies for common applications. The knowledge base simplifies the process of finding relevant academic studies discussing the emergence of the identified Technology Trends and Data Analytics concepts in major construction Application Areas. The visualizations, tabulations, and electronic navigation provided facilitate the pinpointing of areas of research that have greater potential for further investigation. Finally, the evaluation of the results of the literature exploration through the industry survey further endorsed the implications of the literature exploration in practice.

The AEC/FM community has established a strong connection between specific technological trends and Application Areas, such as building information modeling and productivity, and Data Analytics concepts. As a result of the ongoing digital transformation of the industry, similar robust integration is expected between Data Analytics and Technology Trends in various Application Areas as discussed in this paper (McGraw Hill Construction 2014). However, in this study, the authors spotlighted future research directions that the community can take. Such directions go beyond the intersection of BIM and productivity and Data Analytics. For example, the gap between lean construction and Data Analytics offers vast research potential. By performing advanced data analysis on construction data, such as the number and nature of requests for information (RFI), change orders, and cash flow data, the AEC/FM industry has the potential to improve the decision-making process and minimize waste, as defined by lean principles (Forbes and Ahmed 2010), from construction processes. Furthermore, this study illustrates the necessity of further investigations on AR/VR, because both the survey and literature exploration results indicated that there is lack of work in this area and room for exploring the potential of AR/VR integrated with Data Analytics concepts.

Data Availability Statement

Data generated or analyzed during the study are available from the corresponding author by request. Information about the *Journal*'s data-sharing policy can be found here: http://ascelibrary.org/doi/10.1061/(ASCE)CO.1943-7862.0001263.

Acknowledgments

The presented work was partially supported by the California State University East Bay's (CSUEB) Office of Research and Sponsored Programs (ORSP) Faculty Support Grants (FSG). The authors gratefully acknowledge the support from the CSUEB ORSP. Any opinions, findings, conclusions, and recommendations expressed in this paper are those of the authors and do not necessarily represent the views of the CSUEB ORSP.

References

Agarwal, R., S. Chandrasekaran, and M. Sridhar. 2016. "Imagining construction's digital future." Accessed June 24, 2018. https://www.mckinsey.com/industries/capital-projects-and-infrastructure/our-insights/imagining-constructions-digital-future.

Ahn, C. R., S. Lee, and F. Peña-Mora. 2012. "Monitoring system for operational efficiency and environmental performance of construction operations, using vibration signal analysis." In *Proc., Construction Research Congress 2012: Construction Challenges in a Flat World*, 1879–1888. Reston, VA: ASCE.

Akbarnezhad, A., K. C. G. Ong, and L. R. Chandra. 2014. "Economic and environmental assessment of deconstruction strategies using building information modeling." *Autom. Constr.* 37 (Jan): 131–144. https://doi.org/10.1016/j.autcon.2013.10.017.

Akhavian, R., and A. H. Behzadan. 2013. "Simulation-based evaluation of fuel consumption in heavy construction projects by monitoring equipment idle times." In *Proc., 2013 Winter Simulations Conf. (WSC)*, 3098–3108. New York: IEEE.

Akhavian, R., and A. H. Behzadan. 2014. "Evaluation of queuing systems for knowledge-based simulation of construction processes." *Autom. Constr.* 47 (Nov): 37–49. https://doi.org/10.1016/j.autcon.2014.07.007.

Akhavian, R., and A. H. Behzadan. 2015a. "Construction equipment activity recognition for simulation input modeling using mobile sensors and machine learning classifiers." *Adv. Eng. Inf.* 29 (4): 867–877. https://doi.org/10.1016/j.aei.2015.03.001.

Akhavian, R., and A. H. Behzadan. 2015b. "Wearable sensor-based activity recognition for data-driven simulation of construction workers' activities." In *Proc., 2015 Winter Simulation Conf. (WSC)*, 3333–3344. New York: IEEE.

Akhavian, R., and A. H. Behzadan. 2016. "Smartphone-based construction workers' activity recognition and classification." *Autom. Constr.* 71 (Nov): 198–209. https://doi.org/10.1016/j.autcon.2016.08.015.

Akhavian, R., and A. H. Behzadan. 2018. "Coupling human activity recognition and wearable sensors for data-driven construction simulation." *J. Inf. Technol. Constr.* 23 (1): 1–15.

Alhaija, H. A., S. K. Mustikovela, L. Mescheder, A. Geiger, and C. Rother. 2018. "Augmented reality meets computer vision: Efficient data generation for urban driving scenes." *Int. J. Comput. Vision* 126 (9): 961–972. https://doi.org/10.1007/s11263-018-1070-x.

Arayici, Y., P. Coates, L. Koskela, M. Kagioglou, C. Usher, and K. O'Reilly. 2011. "Technology adoption in the BIM implementation for lean architectural practice." *Autom. Constr.* 20 (2): 189–195. https://doi.org/10.1016/j.autcon.2010.09.016.

Armstrong, G., and C. Gilge. 2016. "Building a technology advantage. Harnessing the potential of technology to improve the performance of major projects." In *Proc., Global Construction Survey* San Francisco, CA: KPMG International.

Bates, D., S. Saria, L. Ohno-Machado, A. Shah, and G. Escobar. 2014. "Big data in health care: Using analytics to identify and manage high-risk and high-cost patients." *Health Affair* 33 (7): 1123–1131. https://doi.org/10.1377/hlthaff.2014.0041.

Bilal, M., L. O. Oyedele, O. O. Akinade, S. O. Ajayi, H. A. Alaka, H. A. Owolabi, J. Qadir, M. Pasha, and S. A. Bello. 2016a. "Big data architecture for construction waste analytics (CWA): A conceptual framework." *J. Build. Eng.* 6 (Jun): 144–156. https://doi.org/10.1016/j.jobe.2016.03.002.

Bilal, M., L. O. Oyedele, J. Qadir, K. Munir, S. O. Ajayi, O. O. Akinade, and M. Pasha. 2016b. "Big Data in the construction industry: A review of present status, opportunities, and future trends." *Adv. Eng. Inf.* 30 (3): 500–521. https://doi.org/10.1016/j.aei.2016.07.001.

Blanco, J. L., A. Mullin, K. Pandya, and M. Sridhar. 2017. "The new age of engineering and construction technology." Accessed June 24, 2018. https://www.mckinsey.com/industries/capital-projects-and-infrastructure/our-insights/the-new-age-of-engineering-and-construction-technology.

Bosche, F., and C. T. Haas. 2008. "Automated retrieval of 3D CAD model objects in construction range images." *Autom. Constr.* 17 (4): 499–512. https://doi.org/10.1016/j.autcon.2007.09.001.

Bosché, F. 2010. "Automated recognition of 3D CAD model objects in laser scans and calculation of as-built dimensions for dimensional compliance control in construction." *Adv. Eng. Inf.* 24 (1): 107–118. https://doi.org/10.1016/j.aei.2009.08.006.

Bradley, A., H. Li, R. Lark, and S. Dunn. 2016. "BIM for infrastructure: An overall review and constructor perspective." *Autom. Constr.* 71 (Nov): 139–152. https://doi.org/10.1016/j.autcon.2016.08.019.

Bryde, D., M. Broquetas, and J. M. Volm. 2013. "The project benefits of building information modelling (BIM)." *Int. J. Project. Manage.* 31 (7): 971–980. https://doi.org/10.1016/j.ijproman.2012.12.001.

Cao, M., R. Chychyla, and T. Stewart. 2015. "Big data analytics in financial statement audits." *Account. Horiz.* 29 (2): 423–429. https://doi.org/10.2308/acch-51068.

Castronovo, F., D. Nikolic, Y. Liu, and J. Messner. 2013. "An evaluation of immersive virtual reality systems for design reviews." In *Proc., 13th Int. Conf. on Construction Applications of Virtual Reality*, 47. London: Construction Applications of Virtual Reality.

Chai, J., H.-L. Chi, X. Wang, C. Wu, K. H. Jung, and J. M. Lee. 2016. "Automatic as-built modeling for concurrent progress tracking of plant construction based on laser scanning." *Concurrent Eng.* 24 (4): 369–380. https://doi.org/10.1177/1063293X16670449.

Chang, C.-Y., and M.-D. Tsai. 2013. "Knowledge-based navigation system for building health diagnosis." *Adv. Eng. Inf.* 27 (2): 246–260. https://doi.org/10.1016/j.aei.2012.12.003.

Cheung, F. K., J. Rihan, J. Tah, D. Duce, and E. Kurul. 2012. "Early stage multi-level cost estimation for schematic BIM models." *Autom. Constr.* 27 (Nov): 67–77. https://doi.org/10.1016/j.autcon.2012.05.008.

Dávila Delgado, J. M., I. Brilakis, and C. Middleton. 2015. "Open data model standards for structural performance monitoring of infrastructure assets." In *Proc., CIB W78 Conf.*, 1–10. Amsterdam, Netherlands: Elsevier.

Dimitrov, A., and M. Golparvar. 2014. "Vision-based material recognition for automated monitoring of construction progress and generating building information modeling from unordered site image collections." *Adv. Eng. Inf.* 28 (1): 37–49. https://doi.org/10.1016/j.aei.2013.11.002.

Eadie, R., M. Browne, H. Odeyinka, C. McKeown, and S. McNiff. 2013. "BIM implementation throughout the UK construction project lifecycle: An analysis." *Autom. Constr.* 36 (Dec): 145–151. https://doi.org/10.1016/j.autcon.2013.09.001.

Eastman, C., P. Teicholz, R. Sacks, and K. Liston. 2011. *BIM handbook: A guide to building information modeling for owners, managers, designers, engineers and contractors*. Hoboken, NJ: Wiley.

El-Omari, S., and O. Moselhi. 2008. "Integrating 3D laser scanning and photogrammetry for progress measurement of construction work." *Autom. Constr.* 18 (1): 1–9. https://doi.org/10.1016/j.autcon.2008.05.006.

Fang, D., Y. Chen, and L. Wong. 2006. "Safety climate in construction industry: A case study in Hong Kong." *J. Constr. Eng. Manage.* 132 (6): 573–584. https://doi.org/10.1061/(ASCE)0733-9364(2006)132:6(573).

Feng, C., N. Fredricks, and V. R. Kamat. 2013. "Human-robot integration for pose estimation and semi-autonomous navigation on unstructured construction sites." In *Proc., Int. Symp. on Automation and Robotics in Construction*, 30. Montreal: The International Association for Automation and Robotics in Construction.

Forbes, L. H., and S. M. Ahmed. 2010. *Modern construction: Lean project delivery and integrated practices*. Boca Raton, FL: CRC Press.

Friedman, J., T. Hastie, and R. Tibshirani. 2001. Vol. 1 of *The elements of statistical learning*. New York: Springer.

Golparvar-Fard, M., J. Bohn, J. Teizer, S. Savarese, and F. Peña-Mora. 2011. "Evaluation of image-based modeling and laser scanning accuracy for emerging automated performance monitoring techniques." *Autom. Constr.* 20 (8): 1143–1155. https://doi.org/10.1016/j.autcon.2011.04.016.

Golparvar-Fard, M., S. Savarese, and F. Pena-Mora. 2009. "Interactive visual construction progress monitoring with D4AR-4D augmented reality-models." In *Proc. Construction Research Congress*, 41–50. Reston, VA: ASCE.

Golparvar-Fard, M., P. Tang, Y. K. Cho, and M. K. Siddiqui. 2013. "Grand challenges in data and information visualization for the architecture, engineering, construction, and facility management industries." In *Proc., Computing in Civil Engineering*, 849–856. Reston, VA: ASCE.

Gonsalves, R., and J. Teizer. 2009. "Human motion analysis using 3D range imaging technology." In *Proc., 26th Int. Symp. on Automation and Robotics in Construction*, 76–85. Montreal: The International Association for Automation and Robotics in Construction.

Grilo, A., and R. Jardim-Goncalves. 2010. "Value proposition on interoperability of BIM and collaborative working environments." *Autom. Constr.* 19 (5): 522–530. https://doi.org/10.1016/j.autcon.2009.11.003.

Grilo, A., and R. Jardim-Goncalves. 2011. "Challenging electronic procurement in the AEC sector: A BIM-based integrated perspective." *Autom. Constr.* 20 (2): 107–114. https://doi.org/10.1016/j.autcon.2010.09.008.

Han, K. K., and M. Golparvar-Fard. 2015. "Appearance-based material classification for monitoring of operation-level construction progress using 4D BIM and site photologs." *Autom. Constr.* 53 (May): 44–57. https://doi.org/10.1016/j.autcon.2015.02.007.

Han, S., S. Lee, and F. Peña-Mora. 2012. "Vision-based motion detection for safety behavior analysis in construction." In *Proc., Construction Research Congress*, 21–23. Reston, VA: ASCE.

Jardim-Goncalves, R., and A. Grilo. 2010. "SOA4BIM: Putting the building and construction industry in the single European information space." *Autom. Constr.* 19 (4): 388–397. https://doi.org/10.1016/j.autcon.2009.11.009.

Jiao, Y., Y. Wang, S. Zhang, Y. Li, B. Yang, and L. Yuan. 2013. "A cloud approach to unified lifecycle data management in architecture, engineering, construction and facilities management: Integrating BIMs and SNS." *Adv. Eng. Inf.* 27 (2): 173–188. https://doi.org/10.1016/j.aei.2012.11.006.

Jiao, Y., S. Zhang, Y. Li, Y. Wang, B. Yang, and L. Wang. 2014. "An augmented MapReduce framework for building information modeling applications." In *Proc., 18th Int. Conf. on Computer Supported Cooperative Work in Design*, 283–288. New York: IEEE.

Kao, L. S., and C. E. Green. 2008. "Analysis of variance: Is there a difference in means and what does it mean?" *J. Surg. Res.* 144 (1): 158–170. https://doi.org/10.1016/j.jss.2007.02.053.

Kim, H., and L. Soibelman. 2002. "Knowledge discovery and supervised machine learning in a construction project database." In *WIT transactions on information and communication technologies*, 28. Southampton, UK: WIT Press.

Leite, F., Y. Cho, A. H. Behzadan, S. Lee, S. Choe, Y. Fang, R. Akhavian, and S. Hwang. 2016. "Visualization, information modeling, and simulation: Grand challenges in the construction industry." *J. Comput. Civ. Eng.* 30 (6): 04016035. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000604.

Liao, C. W., and Y. H. Perng. 2008. "Data mining for occupational injuries in the Taiwan construction industry." *Saf. Sci.* 46 (7): 1091–1102. https://doi.org/10.1016/j.ssci.2007.04.007.

Lin, J. R., Z. Z. Hu, J. P. Zhang, and F. Q. Yu. 2016. "A natural-language-based approach to intelligent data retrieval and representation for cloud BIM." *Comput. Aided Civ. Infrastruct. Eng.* 31 (1): 18–33. https://doi.org/10.1111/mice.12151.

Liu, H., M. Lu, and M. Al-Hussein. 2016. "Ontology-based semantic approach for construction-oriented quantity take-off from BIM models in the light-frame building industry." *Adv. Eng. Inf.* 30 (2): 190–207. https://doi.org/10.1016/j.aei.2016.03.001.

Mahfouz, T. S. 2009. "Construction legal support for differing site conditions (DSC) through statistical modeling and machine learning (ML)." Ph.D. thesis, Dept. of Civil, Construction, and Environmental Engineering, Iowa State Univ.

Mao, W., Y. Zhu, and I. Ahmad. 2007. "Applying metadata models to unstructured content of construction documents: A view-based approach." *Autom. Constr.* 16 (2): 242–252. https://doi.org/10.1016/j.autcon.2006.05.005.

Marr, B. 2015. *Big data: Using SMART big data, analytics and metrics to make better decisions and improve performance*. Chichester, UK: Wiley.

Marr, B. 2016. "How big data and analytics are transforming the construction industry." Accessed September 3, 2016. http://www.forbes.com/sites/bernardmarr/2016/04/19/how-big-data-and-analytics-are-transforming-the-construction-industry/#245384ab5cd0.

Mastrolembo Ventura, S., and F. Castronovo. 2018. "An agenda for implementing semi-immersive virtual reality in design meetings involving clients and end-users." In *Proc., European Conf. on Product and Process Modeling*, 1–9. Copenhagen, Denmark: European Conference on Product and Process Modelling.

McGraw-Hill Construction. 2014. *The business value of BIM for construction in major global markets: How contractors around the world are driving innovation with building information modeling*. Smart Market Rep. Bedford, MA: McGraw-Hill Construction.

Park, J., K. Kim, and Y. K. Cho. 2016. "Framework of automated construction-safety monitoring using cloud-enabled BIM and BLE mobile tracking sensors." *J. Constr. Eng. Manage.* 143 (2): 05016019. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001223.

Pärn, E. A., D. J. Edwards, and M. C. P. Sing. 2017. "The building information modelling trajectory in facilities management: A review." *Autom. Constr.* 75 (Mar): 45–55. https://doi.org/10.1016/j.autcon.2016.12.003.

Rawai, N. M., M. S. Fathi, M. Abedi, and S. Rambat. 2013. "Cloud computing for green construction management." In *Proc., 3rd Int. Conf. on Intelligent System Design and Engineering Applications*, 432–435. New York: IEEE.

Redmond, A., A. Hore, M. Alshawi, and R. West. 2012. "Exploring how information exchanges can be enhanced through cloud BIM." *Autom. Constr.* 24 (Jul): 175–183. https://doi.org/10.1016/j.autcon.2012.02.003.

Sanyal, J., and J. New. 2013. "Simulation and big data challenges in tuning building energy models." In *Proc., Workshop on Modeling and Simulation of Cyber-Physical Energy Systems*, 1–6. New York: IEEE.

Shen, Z., P. Tang, O. Kanaan, and Y. Cho. 2013. "As-built error modeling for effective 3D laser scanning on construction sites." In *Proc., Computing in Civil Engineering (2013)*, 533–540. Reston, VA: ASCE.

Soibelman, L., L. Y. Liu, and J. Wu. 2004. "Data fusion and modeling for construction management knowledge discovery." In *Proc., Int. Conf. on Computing in Civil and Building Engineering*. Reston, VA: ASCE.

Song, J., C. T. Haas, C. Caldas, E. Ergen, and B. Akinci. 2006. "Automating the task of tracking the delivery and receipt of fabricated pipe spools in industrial projects." *Autom. Constr.* 15 (2): 166–177. https://doi.org/10.1016/j.autcon.2005.03.001.

Tabachnick, B. G., and L. S. Fidell. 2007. *Experimental designs using ANOVA*. Belmont, CA: Thomson/Brooks/Cole.

Tang, P., E. B. Anil, B. Akinci, and D. Huber. 2011. "Efficient and effective quality assessment of as-is building information models and 3D laser-scanned data." In *Proc., Computing in Civil Engineering*, 486–493. Reston, VA: ASCE.

Turkan, Y., F. Bosche, C. T. Haas, and R. Haas. 2012. "Automated progress tracking using 4D schedule and 3D sensing technologies." *Autom. Constr.* 22 (Mar): 414–421. https://doi.org/10.1016/j.autcon.2011.10.003.

Wood, C. 2016. "Betting on big data: How construction firms are leveraging digitized job sites." Accessed July 1, 2018. https://www.constructiondive.com/news/betting-on-big-data-how-construction-firms-are-leveraging-digitized-job-si/431047/.

Zhai, D., P. M. Goodrum, C. T. Haas, and C. H. Caldas. 2009. "Relationship between automation and integration of construction information systems and labor productivity." *J. Constr. Eng. Manage.* 135 (8): 746–753. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000024.

Zhang, C., V. S. Kalasapudi, and P. Tang. 2016. "Rapid data quality oriented laser scan planning for dynamic construction environments." *Adv. Eng. Inf.* 30 (2): 218–232. https://doi.org/10.1016/j.aei.2016.03.004.