The Status Quo and Future Potentials of Data Analytics in AEC/FM: A Quantitative Analysis of Academic Research and Industry Outlook

Shahrzad Mansouri[1] and Reza Akhavian[2]

[1]Graduate Student, School of Engineering, California State Univ., East Bay, Hayward, CA 94542. E-mail: smansouri@horizon.csueastbay.edu
[2]Assistant Professor, School of Engineering, California State Univ., East Bay, Hayward, CA 94542. E-mail: reza.akhavian@csueastbay.edu

Abstract

In the present era of data analytics, industries leverage the power embedded in the abundant data generated rapidly to improve procedures and facilitate decision making. The architectural, engineering, construction, and facility management (AEC/FM) industry as well, begins to realize the benefits of data-driven approaches. However, AEC/FM is still behind many other industries in leveraging the advantages of data. During the last decade, researchers have focused their attention to emerging construction trends such as building information modeling (BIM). Integrated with data analytics, such trends have high potential to continue the technology evolution of the industry. This paper consolidates the records of current relevant efforts in AEC/FM academic research and evaluates the conclusions from this literature exploration through an industry survey. Following a comprehensive literature review, a three dimensional evidenced taxonomy was developed by categorizing the primary concepts into related segments 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. The same categorization was used to conduct the survey. Statistical analysis of the survey results indicates a general agreement between the literature-based identified technology trends and application areas that can benefit from data. BIM exhibited the most promising Technology Trend when integrated with data analytics in both literature and industry surveys. As for the application areas, process efficiency and productivity improvement ranked the highest in the literature and industry survey, respectively. This study contributes to the body of knowledge and practice by creating an evidenced account of the existing frameworks that benefit from data analytics and future potentials from both the academic and industry standpoints.

INTRODUCTION

Data is turning into the infinite alphabet of computer-based analytical applications. Data analytics generates information that in turn results in data-informed knowledge leading to more appropriate actions. Today's technological advancement manifests the fact that benefits of data-driven and technology-based applications are not limited to certain industries. Architectural, engineering, construction, and facility management (AEC/FM) industry has made a great deal of progress in taking advantage of the new trends during the past few decades (Mantha et al. 2015; Ham et al. 2016; Leite et al. 2016). However, the implementation rate of the new trends in construction industry is lower than others. Comparing to manufacturing, for instance, automation is not as prevalent in construction practice, although the academic community is actively producing promising results on the subject. AEC/FM research on the broad topic of technology has been mainly focused on trends such as building information modeling (BIM), virtual and augmented reality (VR/AR), simulation modeling, and robotics and automation during the past couple of years (Golparvar-Fard et al. 2011; Feng et al. 2013; Akhavian and Behzadan 2015). The introduction of Big Data analytics and associated concepts such as cloud computing and machine learning, however, is creating a visible paradigm shift in the new research topics and funding trends. The power of data analytics supplied with the aforementioned trends has strengthened their effectiveness and application areas of research trends. In contrast to most of the other research areas, industry is not moving with the same pace as the academia in adopting approaches that benefit from the integration of data analytics techniques with new technology trends to accelerate the improvements in different application areas such as safety or productivity (ConstructionDIVE 2016; Forbes 2016).

Given the considerable interest in leveraging the power of data analytics in AEC/FM fields and the fact that such research projects are actively being pursued, this paper presents a taxonomy of existing published studies that employed (1) *Data Analytics* concepts along with (2) *Technology Trends* for (3) specific *Applications Areas* in construction. The developed taxonomy maps recent research studies using the three abovementioned dimensions as a result of an extensive literature search. Furthermore, an investigation of the industry view on this subject has been made by means of a survey questionnaire. The outcome of the two explorations are then studied through statistical analysis to reach a solid conclusion of the status quo and expected implications in the future.

METHODOLOGY

Literature exploration method

Three dimensions have been defined to establish a basis for exploring the literature and development of an evidence-based taxonomy. The first dimension concerns the prevalent “Data Analytics” concepts such as the Big Data and Cloud Computing. For the second dimension, “Technology Trends”, the new technologies with the potential of being integrated effectively with Data Analytics were identified. Finally, in “Application Areas” dimension, key areas of implementation for such integrations are collected. Table 1 shows the components of each dimension that are used and mapped onto each other to discover the research studies in their intersections. In Table 1 BLM used as acronyms for building lifecycle management.

Table 1. Components of the Three Dimensions Defined for the Taxonomy.

Data Analytics	*Technology Trends*	*Applications 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. Regressions Models	5. Laser Scanning	5. BLM
f. Classification Models	6. Sensing & Monitoring	6. Lean Construction
g. Clustering Algorithms		7. Progress Monitoring
h. Cloud Computing		

In determining the components for the Data Analytics dimension, their significance and prevalence in other research domains such as computer science is considered. In a heuristic attempt, those currently investigated in the industry are also included (ConstructionDIVE 2016; Forbes 2016). Finally, it was tried to maintain a level of detail that is neither too fine-grained nor too coarse. For example, machine learning could encompass 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). To develop the taxonomy, a large number of published research studies related to the defined dimensions were explored. Towards this goal, a comprehensive key-words search has been conducted in specialized journals and conference proceedings such American Society of Civil Engineers (ASCE) Journal of Computing in Civil Engineering and Elsevier Science journal of Automation in Construction as well as search engines such as Google Scholar and Engineering Village. Once a related article is found, the bibliography of the article is also scanned to find more relevant papers. This significantly increased the number of papers investigated and enriched the database.

Industry survey method

An electronic survey questionnaire was sent out using Google Forms to more than one hundred industry experts. The survey consists of seven questions in total responding to which was expected to take no more than 10 minutes. In the beginning, it defines data analytics; *"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 ask about the participant's current position and industry experience. The third question is posed to inquire about the participant's experience with the Technology Trends. The next two questions then present Likert scale choices to participants to express their level of agreement on the effectiveness of data analytics concepts when integrated with Technology Trends and Application Areas identified in the academic literature search. This streamlines the quantitative analysis between the two investigations. The Likert scales have been assigned numeric values as *Strongly Disagree = 1, Disagree = 2, Neither Agree Not Disagree = 3, Agree = 4, and Strongly Agree = 5*. The last two questions are of the scope of this paper.

Statistical analysis method

A two-step verification and validation statistical analysis were performed in this research. The verification step leverages the powerful one-way analysis of variance (ANOVA) to test the responses received in the industry survey about 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. Here, the rationale is that if the average between different Technology Trends or Application Areas to the Average within the individual Technology Trends or Application Areas is high, the F statistic will go up and there is a higher chance of rejecting the null hypothesis. The F statistics obtained is compared to the critical value using the available F tables in statistics textbooks to reject the null hypothesis if F (test statistics) > F^{CV} (critical value).

In the validation step, the results of the literature exploration are assessed through standard Student's t-Test. In this process, pairwise t-Tests are performed between the highest ranked Technology Trend/Application Area in the literature exploration with all other groups. This step is to validate whether the high tendency in the academic world towards one group show statistically significant difference between that group and others in the view of industry experts. Similar to ANOVA, in the Student's t-Test a test statistics, t value obtained using Equations (1) and (2) is compared with a critical value to reject the null hypothesis if the calculated t value is greater than the critical t value.

$$t = \frac{\bar{x}_1 - \bar{x}_2}{s_p\sqrt{\frac{1}{n_1}+\frac{1}{n_2}}} \qquad (1)$$

$$s_p = \sqrt{\frac{(n_1-1)s_1^2+(n_2-1)s_2^2}{n_1+n_2-2}} \qquad (2)$$

where $\bar{x}_1$ is the mean of first sample, $\bar{x}_2$ is the mean of second sample, n_1 is sample size of first sample, n_2 is sample size of second sample, s_1 is the standard deviation of first sample, s_2 is the standard deviation of second sample, and s_p is the pooled standard deviation.

RESULTS AND ANALYSIS

Literature exploration results

To present the results of the literature exploration, a three dimensional taxonomy is designed trough a coded grid to represent the identified papers. Specifically, the Technology Trend and Application Areas are assigned to the horizontal and vertical axes of the grid, respectively. Horizontal axis is marked with a number from 1 to 7 and vertical axis is marked 1 to 6 associated with their components according to Table 1. The Data Analytics components are also assigned to each cell using corresponding letters in Table 1.The taxonomy is shown in Figure 1. A color coding scheme shows the extent of using Data Analytics together with the available tools and technologies to solve problems in different application contexts. The darker the cell is, the higher is the frequency of studies in that particular conjunction of three dimensional areas. In this coded grid, certain categories can be extracted by their alphanumeric

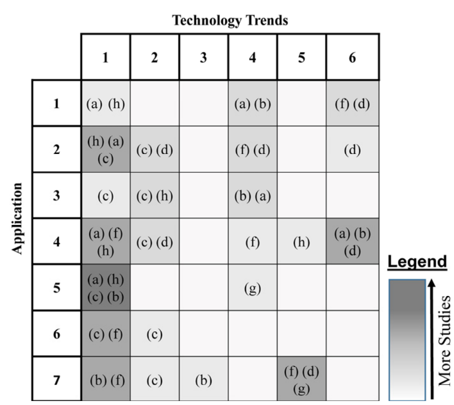


Figure 1. Taxonomy of the studies in three-dimensions

codes. The first characters of each code is the corresponding letter to the Data Analytics component in Table 1. The two other characters are numbers corresponding to the Technology Trends and Application Areas as per Table 1. For instance, code *a-1-1* refers to a study that uses *Big Data* and *BIM* for project *Safety*. Finally, all those papers and denoting codes are tabulated in Table 2.

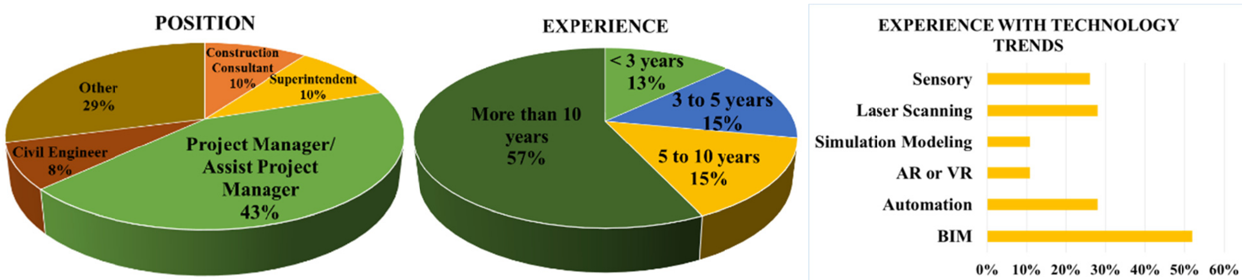
Table 2. Category Codes of the Developed Taxonomy and the Corresponding Publications.

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

As it is shown in Figure 1, within the Technology Trends, the ***BIM*** category shows ***the most potential for integration with Data Analytics*** concepts. In the Application Areas, ***Process Efficiency***, has ***benefited the most from Data Analytics techniques*** specially when combined with BIM or Sensing & Monitoring.

Industry survey results

Out of more than 100 industry experts invited to participate, 54 responses were received. Figure 2 illustrates participants' position, construction industry experience, and their background in working with the Technology Trends. As shown in this figure, around half of the participants are in the level of project manager or assistant project manager. Also, around 60% of them has more than 10 years of experience in the construction industry. 52% reported having experience with BIM while simulation modeling and AR/VR had the lowest number with only 11%.



(a) (b) (c)

Figure 2. Participants' (a) position, (b) construction experience, and technology experience

In response to the question about ranking the Technology Trends on their effectiveness when integrated with Data Analytics concepts, *BIM* turned out to be the *first-ranked technology* with the average score of 4.02 out of 5 while AR/VR was the last with the average of 3.55 out of 5. On the Application Area side where the question asked about the level of agreement on the effectiveness of data analytics and technology trends integration, *Productivity was ranked first* with the average score of 4.26 out of 5 and *Building Lifecycle Management (BLM) was ranked last* with 3.81 out of 5. Table 3 shows the rankings and average and standard deviation of the scores.

Table 3. Summary of Scores for Technology Trends and Application Areas

Technology Trends	**BIM**	**Automation**	**AR & VR**	**Simulation Modeling**	**Laser Scanning**	**Sensing & Monitoring**	
Average	*4.02*	3.70	*3.55*	3.79	3.79	3.74	
Standard Deviation	0.93	0.91	0.87	0.93	0.88	0.92	
Application Areas	**Safety**	**Productivity**	**Sustain-ability**	**Process Efficiency**	**BLM**	**Lean Construction**	**Progress Monitoring**
Average	4.11	*4.26*	3.89	4.04	*3.81*	3.87	4.15
Standard Deviation	0.96	0.87	0.92	0.91	0.95	1.01	0.94

Statistical analysis results

As mentioned in the Methodology Section, ANOVA and Student's t-Test were applied on the survey responses for verification and validation purposes between the literature exploration and industry survey. For the ANOVA, the null hypothesis was set as H_0: *all population means are equal.* With 95% confidence interval ($\alpha = 0.05$) the hypothesis was tested and the results are shown in Table 4 for both the Technology Trends and Application Areas. Furthermore, since the results of the literature exploration reveals that *BIM* and *Process Efficiency* have the most potential in the Data Analytics domain, each has been compared pairwise using Student's t-Test with other Technology Trends and Application Areas, respectively. Results are shown in Tables 5 and 6. The null hypothesis here is H_0: *the two means are equal* and the confidence level is 95% (α = 0.05). The *t clerical value* is 1.98 for both the Technology Trends and for Application Areas.

Table 4. ANOVA Test Statistics and Decisions

	F	F^{CV}	Decision
Technology Trends	1.53	2.24	*Not reject*
Application Areas	1.67	2.12	*Not reject*

Table 5. Pairwise Student's t-Test Summary for BIM vs. other Technology Trends

Technology Trends	Automation	AR/VR	Simulation	Laser Scan	Sensing
t statistics	1.79	2.70	1.26	1.28	1.57
Decision	*Do not reject*	*Reject*	*Do not reject*	*Do not reject*	*Do not reject*

Table 6. Pairwise Student's t-Test Summary for Process Improvement vs. 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
Decision	*Do not reject*	*Do not reject*	*Do not reject*	*Do not reject*	*Do not reject*	*Do not reject*

DISCUSSION OF RESULTS

In the literature exploration, around half of the cells in the taxonomy developed are not populated with any component of Data Analytics dimension. This essentially translates to the lack of research and abundance of opportunities in those areas. BIM has been chosen as having the highest potential to be effective when used together with data-driven approaches. Considering the simple integration of BIM tools with building data and numerous important applications such as collaborative design and clash detection, this was expected. Surprisingly, AR & VR and to a lesser extent Laser Scanning show the lowest integration potential with Data Analytics approaches in the literature. This can be justified by the fact that such research topics possibly fall under the category of computer vision are still emerging in the computer science discipline and have not made their way to the construction world. As such, a demanding research potential is revealed that calls for frameworks that encompass visualization techniques through AR/VR and data-driven applications. Process Efficiency, presented the most applicable area of implementation for integrated frameworks of technology and data analytics. This might be partially because of the broad definition of Process Efficiency which includes many different processes within the AEC/FM domain. On the other hand, Lean Construction turns out to have the lowest rate of implementation for such integrated systems. Again, there is yet a huge potential for transforming traditional methods of applying lean principles such as the pull planning practice using data analytics. The ANOVA test reveals that no statistically significant difference is observed among the Technology Trends identified in the literature as for their ability to effectively combine with Data Analytics concepts based on the industry survey responses. Similar trend is observed in the result if the ANOVA test on the industry survey responses for Application Areas. This result confirms the veracity of the choices extracted from the literature. It also indicates that the research community and industry professionals have similar evaluation of the effectiveness of integration of data-driven decision making strategies for different applications in the industry. As for the pairwise Student's t-Test, although BIM had the highest average in the industry survey too, its average appears to have no significant difference with the other Technology Trends except for AR/VR. This completely mimics the results achieved in the Literature Exploration. Process Improvement average score on the other hand shows no significant difference with other application areas.

CONCLUSION

Data Analytics concepts, Technology Trends, and Application Areas are the three main areas of focus in a comprehensive review of the existing literature and industry survey within AEC/FM in this research study. This detailed analysis provides a simple yet comprehensive knowledgebase for pinpointing relevant research studies in the prevalent Data Analytics areas that use trending technologies for the common applications. This knowledgebase simplifies the process of finding relevant academic studies discussing the emergence of identified Technology Trends and Data Analytics concepts in major construction Application Areas. The literature exploration findings presented in the knowledgebase are evaluated through the industry survey that further endorses their implications in practice. Results indicate that there are several areas of research that can benefit from the integration of emerging Data Analytics approaches such as Machine Learning (i.e. Classification and Prediction Models) and Cloud Computing with current technologies used in construction to improve processes. Some technologies such as BIM show abundance of existing research and some such as AR/VR call for further developments. Also, there are applications such as Lean Construction that are ripe for disruption in AEC/FM industry.

REFERENCES

Ahn, C. R., Lee, S., and Peña-Mora, F. "Monitoring System for Operational Efficiency and Environmental Performance of Construction Operations, Using Vibration Signal Analysis." *Proc., Construction Research Congress 2012*, 21-23.

Akbarnezhad, A., Ong, K. C. G., and Chandra, L. R. (2014). "Economic and environmental assessment of deconstruction strategies using building information modeling." *Autom. Constr.*, 37, 131-144.

Akhavian, R., and Behzadan, A. H. (2014). "Evaluation of queuing systems for knowledge-based simulation of construction processes." *Autom. Constr.*, 47, 37-49.

Akhavian, R., and Behzadan, A. H. (2015). "Construction equipment activity recognition for simulation input modeling using mobile sensors and machine learning classifiers." *Adv. Eng. Inf.*, 29(4), 867-877.

Akhavian, R., and Behzadan, A. H. (2016). "Smartphone-based construction workers' activity recognition and classification." *Autom. Constr.*, 71, 198-209.

Arayici, Y., Coates, P., Koskela, L., Kagioglou, M., Usher, C., and O'reilly, K. (2011). "Technology adoption in the BIM implementation for lean architectural practice." *Autom. Constr.*, 20(2), 189-195.

Bilal, M., Oyedele, L. O., Akinade, O. O., Ajayi, S. O., Alaka, H. A., Owolabi, H. A., Qadir, J., Pasha, M., and Bello, S. A. (2016). "Big data architecture for construction waste analytics (CWA): A conceptual framework." *Journal of Building Engineering*, 6, 144-156.

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.

Bryde, D., Broquetas, M., and Volm, J. M. (2013). "The project benefits of building information modelling (BIM)." *Int. J. Project Manage.*, 31(7), 971-980.

Chai, J., Chi, H.-L., Wang, X., Wu, C., Jung, K. H., and Lee, J. M. (2016). "Automatic as-built modeling for concurrent progress tracking of plant construction based on laser scanning." *Concurrent Engineering*, 24(4), 369-380.

Chang, C.-Y., and Tsai, M.-D. (2013). "Knowledge-based navigation system for building health diagnosis." *Adv. Eng. Inf.*, 27(2), 246-260.

Cheung, F. K., Rihan, J., Tah, J., Duce, D., and Kurul, E. (2012). "Early stage multi-level cost estimation for schematic BIM models." *Autom. Constr.*, 27, 67-77.

ConstructionDIVE (2016). "Betting on big data: How construction firms are leveraging digitized job sites." <http://www.constructiondive.com/news/betting-on-big-data-how-construction-firms-are-leveraging-digitized-job-si/431047/>. (December, 2016).

Dávila Delgado, J. M., Brilakis, I., and Middleton, C. (2015). "Open data model standards for structural performance monitoring of infrastructure assets."

Dimitrov, A., and Golparvar, M. (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.

El-Omari, S., and Moselhi, O. (2008). "Integrating 3D laser scanning and photogrammetry for progress measurement of construction work." *Autom. Constr.*, 18(1), 1-9.

Feng, C., Fredricks, N., and Kamat, V. R. (2013). "Human-robot integration for pose estimation and semi-autonomous navigation on unstructured construction sites." *Ann Arbor*, 1001, 48109.

Forbes (2016). "How Big Data And Analytics Are Transforming The Construction Industry." <http://www.forbes.com/sites/bernardmarr/2016/04/19/how-big-data-and-analytics-are-transforming-the-construction-industry/#245384ab5cd0>. (September 3, 2016).

Friedman, J., Hastie, T., and Tibshirani, R. (2001). *The elements of statistical learning*, Springer series in statistics Springer, Berlin.

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

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

Gonsalves, R., and Teizer, J. "Human motion analysis using 3D range imaging technology." *Proc., Proceedings of the 26th International Symposium on Automation and Robotics in Construction, Austin, Texas*, 76-85.

Grilo, A., and Jardim-Goncalves, R. (2010). "Value proposition on interoperability of BIM and collaborative working environments." *Autom. Constr.*, 19(5), 522-530.
Grilo, A., and Jardim, R. (2011). "Challenging electronic procurement in the AEC sector: A BIM-based integrated perspective." *Autom. Constr.*, 20(2), 107-114.
Ham, Y., Han, K. K., Lin, J. J., and Golparvar-Fard, M. (2016). "Visual monitoring of civil infrastructure systems via camera-equipped Unmanned Aerial Vehicles (UAVs): a review of related works." *Visualization in Engineering*, 4(1), 1.
Han, K. K., and Golparvar-Fard, M. (2015). "Appearance-based material classification for monitoring of operation-level construction progress using 4D BIM and site photologs." *Autom. Constr.*, 53, 44-57.
Han, S., Lee, S., and Peña-Mora, F. "Vision-based motion detection for safety behavior analysis in construction." *Proc., 2012 Construction Research Congress (CRC)*, 21-23.
Jardim-Goncalves, R., and Grilo, A. (2010). "SOA4BIM: Putting the building and construction industry in the Single European Information Space." *Autom. Constr.*, 19(4), 388-397.
Jiao, Y., Wang, Y., Zhang, S., Li, Y., Yang, B., and Yuan, L. (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.
Jiao, Y., Zhang, S., Li, Y., Wang, Y., Yang, B., and Wang, L. "An augmented MapReduce framework for Building Information Modeling applications." *Proc., Computer Supported Cooperative Work in Design (CSCWD), Proceedings of the 2014 IEEE 18th International Conference on*, IEEE, 283-288.
Kim, H., and Soibelman, L. (2002). "Knowledge discovery and supervised machine learning in a construction project database." *WIT Transactions on Information and Communication Technologies*, 28.
Leite, F., Cho, Y., Behzadan, A. H., Lee, S., Choe, S., Fang, Y., Akhavian, R., and Hwang, S. (2016). "Visualization, Information Modeling, and Simulation: Grand Challenges in the Construction Industry." *J. Comput. Civil Eng.*, 04016035.
Liao, C.-W., and Perng, Y.-H. (2008). "Data mining for occupational injuries in the Taiwan construction industry." *Saf. Sci.*, 46(7), 1091-1102.
Lin, J. R., Hu, Z. Z., Zhang, J. P., and Yu, F. Q. (2016). "A Natural-Language-Based Approach to Intelligent Data Retrieval and Representation for Cloud BIM." *Computer-Aided Civil and Infrastructure Engineering*, 31(1), 18-33.
Liu, H., Lu, M., and Al-Hussein, M. (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.
Mahfouz, T. S. (2009). "Construction legal support for differing site conditions (DSC) through statistical modeling and machine learning (ML)."
Mantha, B., Feng, C., Menassa, C. C., and Kamat, V. R. "Real-time building energy and comfort parameter data collection using mobile indoor robots." *Proc., Proceedings of the International Symposium on Automation and Robotics in Construction (ISARC), Oulu, Finland*, 15-18.
Mao, W., Zhu, Y., and Ahmad, I. (2007). "Applying metadata models to unstructured content of construction documents: A view-based approach." *Autom. Constr.*, 16(2), 242-252.
Park, J., Kim, K., and Cho, Y. K. (2016). "Framework of automated construction-safety monitoring using cloud-enabled BIM and BLE mobile tracking sensors." *J. Constr. Eng. Manage.*, 143(2), 05016019.

Rawai, N. M., Fathi, M. S., Abedi, M., and Rambat, S. "Cloud computing for green construction management." *Proc., Intelligent System Design and Engineering Applications (ISDEA), 2013 Third International Conference on*, IEEE, 432-435.

Redmond, A., Hore, A., Alshawi, M., and West, R. (2012). "Exploring how information exchanges can be enhanced through Cloud BIM." *Autom. Constr.*, 24, 175-183.

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

Shen, Z., Tang, P., Kanaan, O., and Cho, Y. (2013). "As-built error modeling for effective 3D laser scanning on construction sites." *Comput. Civil Eng*, 2013, 533-540.

Soibelman, L., Liu, L. Y., and Wu, J. "Data fusion and modeling for construction management knowledge discovery." *Proc., International Conference on Computing in Civil and Building Engineering, Weimar, Germany*.

Tabachnick, B. G., and Fidell, L. S. (2007). *Experimental designs using ANOVA*, Thomson/Brooks/Cole.

Tang, P., Anil, E. B., Akinci, B., and Huber, D. (2011). "Efficient and effective quality assessment of as-is building information models and 3D laser-scanned data." *Computing in Civil Engineering (2011)*, 486-493.

Turkan, Y., Bosche, F., Haas, C. T., and Haas, R. (2012). "Automated progress tracking using 4D schedule and 3D sensing technologies." *Autom. Constr.*, 22, 414-421.

Zhai, D., Goodrum, P. M., Haas, C. T., and Caldas, C. H. (2009). "Relationship between automation and integration of construction information systems and labor productivity." *J. Constr. Eng. Manage.*, 135(8), 746-753.

Zhang, C., Kalasapudi, V. S., and Tang, P. (2016). "Rapid data quality oriented laser scan planning for dynamic construction environments." *Adv. Eng. Inf.*, 30(2), 218-232.