Visualization, Information Modeling, and Simulation: Grand Challenges in the Construction Industry

Fernanda Leite, M.ASCE[1]; Yong Cho, A.M.ASCE[2]; Amir H. Behzadan, A.M.ASCE[3]; SangHyun Lee, M.ASCE[4]; Sooyoung Choe[5]; Yihai Fang[6]; Reza Akhavian, S.M.ASCE[7]; and Sungjoo Hwang, A.M.ASCE[8]

Abstract: With the rapid advancement of sensing and computing technology and the wide adoption of mobile computing, the construction industry has faced a rise in the amount of information and data generated during the lifecycle of the construction project. To deal with a large variety of project data and information to support efficient and effective decision making, visualization, information modeling, and simulation (VIMS) has become critical in the development of capital facilities and infrastructures. The objective of this paper is to identify and investigate grand challenges in VIMS for the construction industry, to assist the academic and industry communities in establishing a future research agenda to solve VIMS challenges. In particular, 17 VIMS grand challenges were identified by an expert task force in the VIMS committee of the ASCE Computing and Information Technology Division, and then VIMS experts in the civil and construction areas from both academia and industry participated in a survey to assess the identified challenges, examine the relative importance of the identified challenges, and investigate current practices and future directions of VIMS. The survey results indicate that several knowledge gaps regarding VIMS challenges between academia and industry still exist, and it is the contention of this research that these particular gaps need to be addressed in future research. These research directions apply to technical issues and sociological/cultural/organizational issues in VIMS challenges. The major contribution of this paper is its claim that the provision of shared views on VIMS challenges lays a firm foundation in which collaborative actions between academia and industry can take place, which will, in turn, advance VIMS for the construction industry. By incorporating the whole project lifecycle, not only project execution but also planning, operation, and maintenance, the analysis provides meaningful hints for VIMS challenges in architecture, engineering, and facility management industries. **DOI: 10.1061/(ASCE)CP.1943-5487.0000604.**

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[1]Associate Professor, Construction Engineering and Project Management Program, Dept. of Civil, Architectural and Environmental Engineering, Univ. of Texas at Austin, 301 E. Dean Keeton St. Stop C1752, Austin, TX 78712-1094. E-mail: fernanda.leite@utexas.edu

[2]Associate Professor, School of Civil and Environmental Engineering, Georgia Institute of Technology, 790 Atlanta Dr. NW, Atlanta, GA 30332-0355. E-mail: yong.cho@ce.gatech.edu

[3]Associate Professor, Dept. of Technology and Construction Management, Missouri State Univ., 901 S. National Ave., Springfield, MO 65897. E-mail: abehzadan@missouristate.edu

[4]Associate Professor, Tishman Construction Management Program, Dept. of Civil and Environmental Engineering, Univ. of Michigan, 2350 Hayward St., Suite 2340 G.G. Brown Bldg., Ann Arbor, MI 48109 (corresponding author). E-mail: shdpm@umich.edu

[5]Ph.D. Candidate, Construction Engineering and Project Management Program, Dept. of Civil, Architectural and Environmental Engineering, Univ. of Texas at Austin, 301 E. Dean Keeton St. Stop C1752, Austin, TX 78712-1094. E-mail: sooyoung.choe@utexas.edu

[6]Ph.D. Student, School of Civil and Environmental Engineering, Georgia Institute of Technology, 790 Atlanta Dr. NW, Atlanta, GA 30332-0355. E-mail: yihaifang@gatech.edu

[7]Assistant Professor, Construction Management Program, School of Engineering, California State Univ. East Bay, Hayward, CA 94542. E-mail: reza.akhavian@csueastbay.edu

[8]Postdoctoral Research Fellow, Tishman Construction Management Program, Dept. of Civil and Environmental Engineering, Univ. of Michigan, 2350 Hayward St., Suite 1316 G.G. Brown Bldg., Ann Arbor, MI 48109. E-mail: sungjoo@umich.edu

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Introduction

In today's construction industry, project teams collect and deal with a large variety of project data and information to support efficient and effective decision making. For many years, sensors and computers have been playing increasingly important roles in capital project development. With the wide adoption of mobile computing in the construction industry, we have now entered into an era in which information and data are ubiquitously generated and distributed. Consequently, project organizations have been drowning in large volumes of data in a variety of formats. With the rising amount of information and data generated in the construction project lifecycle, visualization, information modeling, and simulation (VIMS) has become critical in designing, engineering, constructing, operating, and maintaining capital facilities and infrastructures for supporting various decision-making tasks in construction projects. Hence, at this time it is crucial to investigate what grand challenges exist in VIMS as a result of the unprecedented challenges faced by today's construction projects, and the rapid advancement of new techniques in the fields of VIMS.

This paper accompanies the mission of the ASCE's VIMS Committee, which is to advance research and education in the fields of data visualization, information modeling, and simulation in the construction industry. Specifically, the paper aims to present critical VIMS grand challenges and then provide investigations, discussions, and evaluations of these challenges for the construction industry as derived from the expert survey on both academic and industry practitioners. Analysis of this research deals with VIMS challenges throughout the entire construction project lifecycle, including project planning, execution, monitoring and control, and

operation and maintenance. Because project planning and operation and maintenance stages are not set apart from architecture, engineering and facility management, respectively, along with the construction industry, this paper partly covers architecture, engineering, and facility management industries in the analysis by providing useful hints for VIMS challenges in these industries.

The paper is organized as follows: The first section provides an overview of the motivation for and necessity of this work. The second section presents a scope and a method for the identification of VIMS grand challenges, and the third section presents current practices for each of the three knowledge areas, including applications, benefits, and barriers. The fourth section describes the detailed investigations and evaluations of grand challenges associated with each area. Finally, the fifth section summarizes the findings and discusses potential future directions.

Scope and Methods

The identification of VIMS grand challenges is based on a preliminary discussion on VIMS challenges in the ASCE VIMS Committee and an expert survey from academia and industry. The major motivation of the discussion is today's U.S. construction industry, facing the aging facilities and infrastructures while thinking about the effective delivery of the capital projects. Considering the capability of VIMS in addressing these issues, the scope of this paper is to investigate overall issues that the research and practical area of VIMS in the construction are experiencing today and could be addressed in the future, for the technical advancement and adoption of VIMS throughout the lifecycle of the facility/infrastructure construction project.

Included in the scope of VIMS challenges are technical issues related to facility/infrastructure data collection, modeling, analysis, and representation, in addition to human computer interactions and software interoperability, to manage a large variety of data produced throughout the entire project lifecycle. The scope also involves sociological/cultural/organizational issues such as budget, creditability, decision support process, and/or education and research cooperation issues, because both technical and adoption issues should be taken into account as a whole for a successful application of VIMS to the construction industry. Therefore, the authors developed survey questions that can be useful for investigating all of these issues and that are specific to academic and industry practitioners, who are the survey respondents.

Identification of VIMS Grand Challenges

Initial discussions on grand challenges related to VIMS were held at a VIMS Committee annual meeting. During the 2012 ASCE International Workshop on Computing in Civil Engineering (IWCCE) in Clearwater Beach, Florida, 35 VIMS Committee members were asked in a breakout brainstorming session to list their top three VIMS grand challenges. They included 27 university professors, researchers, and lab directors working on VIMS in departments of architecture, architectural engineering, civil engineering, and construction management, as well as eight industrial practitioners in the field of VIMS technology and construction. The collective feedback received from all members was compiled into a list of 25 grand challenges. Next, committee members were divided into three focus groups including visualization, information modeling, and simulation, by the area of their interests. Three groups then grouped and sorted the list of identified VIMS grand challenges by culminating with 17 grand challenges for each of the three knowledge areas (i.e., six for visualization, five for information modeling, and six for simulation), as given in Table 1 (Golparvar-Fard et al. 2013; Leite et al. 2013; Lee et al. 2013). Each of the aforementioned challenges will be discussed in the "Grand Challenges" section.

Table 1. List of Grand Challenges for VIMS Areas

Area	Challenges
Visualization (V)	• Budget (e.g., software license, hardware) • Disconnect between state-of-the-art and state-of-the-practice • Output formats and mediums suited for construction • Processes for supporting decision making • Real-time remote site modeling • Timely as-built modeling for decision support
Information modeling (IM)	• Big data sources shared across the project lifecycle • Data format and interoperability to enable data sharing • Formalizing (and capturing) as-built data • Modeling for stakeholders across the project lifecycle • Modeling expected facility/infrastructure behavior, especially occupant/user behavior
Simulation (S)	• Credibility and adoption by industry practitioners for decision making • Generating models that adapt to real-world changes • Incorporation of human/occupant behavior into simulation models • Integration into school curricula to educate future engineers • Limited multidisciplinary skills and research cooperation • Verification and validation of simulation output

Expert Survey

Following the groupings of VIMS challenges, an expert survey was devised and deployed to investigate the relative importance of the identified challenges and to collect associated factors regarding current practices and future directions. The initial list of questions was developed by the VIMS executive committee members and modified based on early reviews by selecting two academic and two industry practitioners per each knowledge area (i.e., total 12 practitioners for three areas) who are specialized in the VIMS technology, construction research and practice, and survey design. With the finalized questionnaire, a web-based survey was designed and distributed through e-mail to more than 100 academic and industry practitioners who were familiar with the VIMS knowledge areas. The e-mail lists of academic and industrial societies and various companies (e.g., ASCE, Austin and Houston BIM Group, Virtual Builders) were used to distribute the survey questionnaire. The survey first asked respondents to indicate whether they belonged to academia or industry, followed by their job title and area of expertise (i.e., visualization, information modeling, and/or simulation). Then, depending on their selection (which could be one or a combination of the three areas), respondents were directed to general questions for both academia and industry, including ranking the challenges related to each knowledge area, and current application, benefit, and barriers for VIMS in the construction industry throughout the project lifecycle. In addition, they were asked to respond to specific questions for each knowledge area (e.g., commonly used forms of visual representation in visualization area, interoperability in information model, use of simulation in decision making). Detailed information of the survey questionnaire can be found on the following website: https://utexas.qualtrics.com/SE/?SID=SV_0P1BOLlqH0DGPTT.

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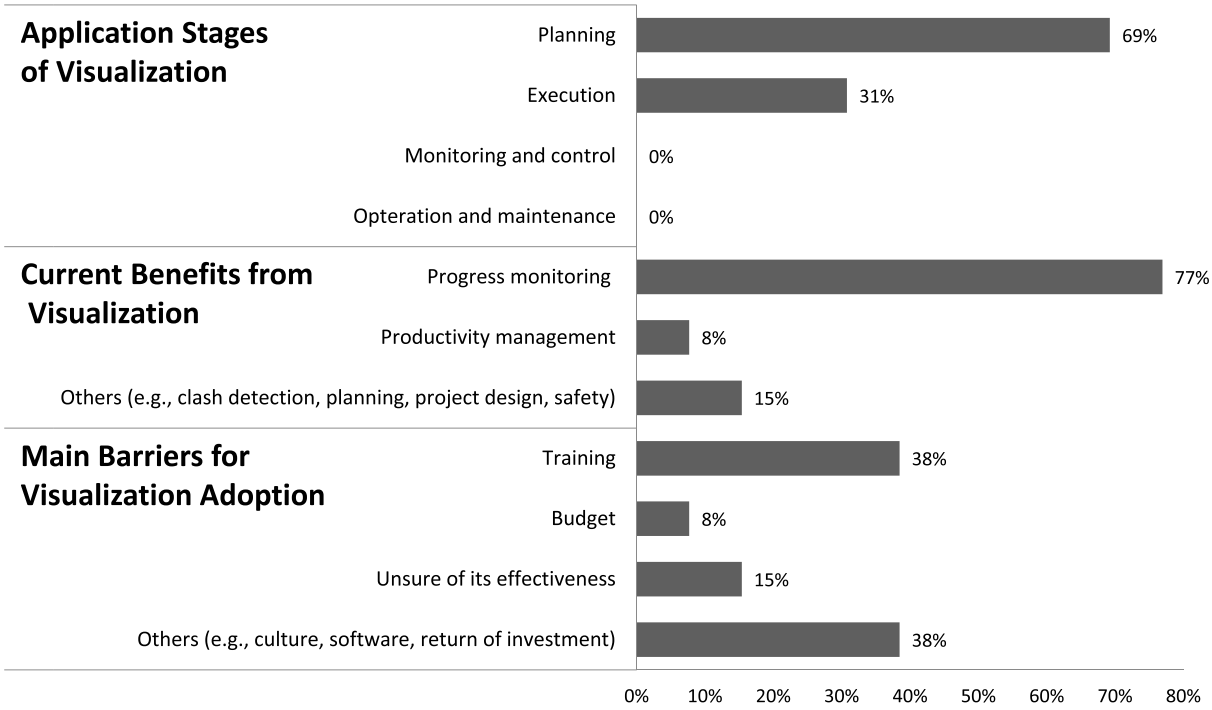

Fig. 1. Summary of current practices of visualization

Survey responses were collected between November 2014 and January 2015. During this period, 62 respondents consisting of both academic and industry practitioners completed the survey. The 31 respondents in academia included 25 university professors in architecture and design, architectural and civil engineering, and construction management, and six other lab directors, whereas 31 respondents in the industry involved diverse professionals in VIMS technology and the construction industry, such as building information modeling (BIM) managers, virtual design and construction (VDC) coordinators, project managers, business development managers, and applied technology directors. As mentioned previously, a respondent could participate in more than one area of expertise. Therefore, 62 respondents provided a total of 96 valid inputs for three areas of expertise: 56 from academia and 40 from industry. In the visualization knowledge area, 19 were academics and 13 were industry practitioners. Among the 37 respondents who provided input for information modeling, 20 were academics and 17 were industry practitioners. For simulation, 17 were academics and 10 were industry practitioners.

Current Practices

This section discusses the current practices of VIMS in the construction industry based on the survey results and the corresponding literature. Specifically, current applications, benefits, and main barriers of VIMS are investigated for each of the three knowledge areas. A detailed discussion on each knowledge area is presented in following subsections.

Visualization

Practitioners in the construction industry need to make timely and high-quality decisions based on a large number of data sets [e.g., drawings, schedule and cost data, resource quantity, three-dimensional (3D) image] from various sources. Visualization techniques hold significant potential to represent these large data sets of construction information in a number of forms that provide valuable insight into various construction domains. Based on the survey of industry practitioners, Fig. 1 summarizes current practices of visualization. As shown in Fig. 1, visualization is used most in the planning stage, including the design and engineering phases (69%) and execution stage (31%) during the project lifecycle. This result implies that effective visual representation of project information at an initial stage assists better project plans by foreseeing unseen information. However, respondents indicated more benefits of visualization if used in progress monitoring (77%) and productivity management (8%). This result demonstrates that visualization has the high potential for wider uses throughout the lifecycle of the capital projects, including not only the planning stage but also the execution, monitoring, and control stages. An enhanced view of current progress can be a basis for implementing appropriate corrective actions, which can lead to project success. In addition, spatial and temporal conflict resolution is another promising domain of visualization. In the additional survey question on the most suitable form of visual representations, 3D models (95%) are therefore currently recognized as the most commonly used form, with other forms of two-dimensional (2D) drawings, charts, and images.

The use of visualization has spread to many construction activities, as revealed in another survey result that 73% of the respondents are currently using visualization tools to support diverse decision-making tasks in their organizations. Examples of such visualization applications are building information modeling (BIM) for clash detection, charts, histograms for benchmarking, schedule variance checking, and design coordination. Visualization representation may advance construction communication, collaboration, and coordination in general, but its level of acceptance varies in different construction management tasks. From another survey's results, current visualization representations used in the design and construction phases focus primarily on scheduling (85%) and as-built visualization (62%).

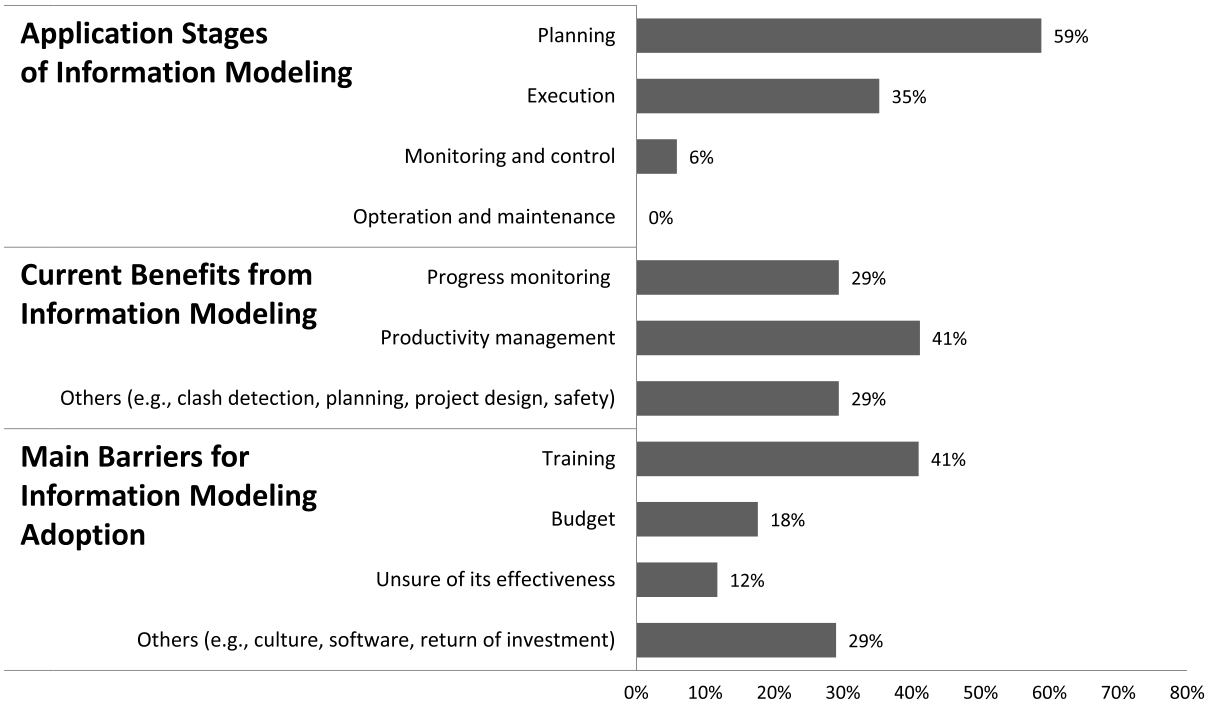

Fig. 2. Summary of current practices of information modeling

However, the area of visualization representations can be extended with diverse perspectives (e.g., cost, safety, environment, or organization views) for wider application of visualization if some barriers during visualization adoption are resolved. As shown in Fig. 1, these barriers include lack of training (38%), uncertain effectiveness (15%), and others (38%) (e.g., budget constraints, cultural inertia, software availability).

Information Modeling

An information model contains various project information such as geometry, spatial relationships, project schedule, cost estimates, and other properties of model elements. Information modeling is a virtual process that encourages the integration of all stakeholders in a project for a more accurate and efficient collaboration than traditional processes. From the survey, it was identified that an information model can incorporate several applications such as (1) meta information of data and documents for searching the information based on keywords, labels, or for linking data sets and navigating from one data set to another (70%); (2) spatial information for spatial planning and clash analysis (40%); (3) temporal information for scheduling, four-dimensional (4D) planning and coordination (40%); and (4) organizational information for supporting decisions (40%).

Information modeling is a continuous process throughout the project lifecycle. As the model is created, team members are constantly refining and adjusting their portions according to project specifications and design changes to ensure the model is as accurate as possible before the project physically breaks ground. As shown in Fig. 2, industry practitioners identified that information modeling is widely used in the planning (59%) and project execution (35%) stages, and have important benefits for productivity management (41%). Survey respondents additionally indicated that data exchange between different stakeholders (58%) and communication enhancement (6%) are critical benefits that result from adopting information modeling. Furthermore, the application area of information modeling can be much wider if existing barriers are overcome such as insufficient training (41%) and budgetary constraints (18%), uncertain effectiveness (12%), and others (29%) (e.g., cultural issues, lack of oversight, lack of software functions), as shown in Fig. 2.

Simulation

A simulation model emulates the operation of an existing or planned process or system over time. The behavior of the process or system to be simulated can be predicted by performing experiments on the model and observing the results (Banks 1998). In the context of construction, simulation can be a key decision-support tool for the quantitative analysis of operations and processes that take place during the project lifecycle. Resources, rules, managerial decisions, and stochastic events consisting of and required to carry out a construction project are also considered in the corresponding simulation model.

Simulation models that are used in the planning and analysis of construction projects represent how various construction operations will perform with regard to key statistical performance measurements. Such measurements often include project cost, time, resource allocation/use, and waiting times of project entities (Ioannou and Martinez 1996; Hajjar and AbouRizk 2002; Akhavian and Behzadan 2014). As shown in Fig. 3, industry practitioners stated that simulation is widely used in diverse project stages including planning (60%), monitoring and control (20%), project execution (10%), and operation and maintenance (10%). Simulation modeling has been used in different application areas such as productivity and progress monitoring (Zayed and Halpin 2004; Golparvar-Fard et al. 2009a), which are also identified from the survey results shown in Fig. 3. Following an increased positive awareness and advancement in technology, simulation modeling has also been expanded to new practice domains such as safety and facility management (Wang et al. 2006; Han et al. 2014b). Although the benefits of simulation modeling to the construction

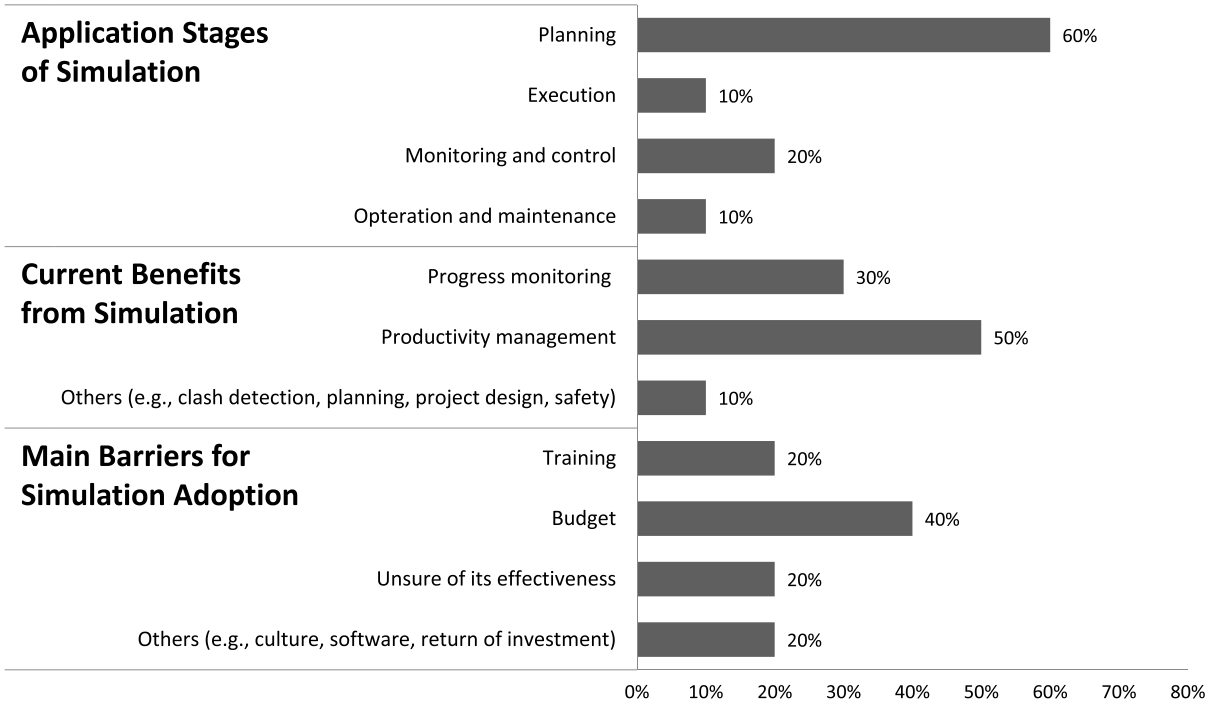

Fig. 3. Summary of current practices of simulation modeling

industry are widely acknowledged, large-scale adoption is still challenging because of existing barriers such as budgetary constraints (40%), insufficient training (20%), uncertain effectiveness (20%), and others (20%) (e.g., cultural issues, limited expertise), as documented in literature (Martinez 2009) and shown in the survey results of Fig. 3.

Grand Challenges

As a relatively new paradigm within the construction industry, VIMS has the potential to enhance decision making, leveraging large amounts of information and data generated in the project lifecycle. With paradigm shifts and emerging technologies, this section discusses detailed challenges identified in Table 1 based on the literature and the results of the expert survey. Specifically, experts from academia and the industry were asked in this survey to rank the grand challenges in each knowledge area (i.e., six for visualization, five for information modeling, and six for simulation). Results were then normalized into five-point scales (i.e., relative importance score from 1, least important, to 5, most important) to examine the relative importance of the challenges. Specifically, six-point scales in visualization and simulation for six challenges in these knowledge areas were converted to five-point scales based on the general method to transform scores between two different measurement lengths (Card 2011). Based on these results, the following sections describe the investigation of the grand challenges in each VIMS knowledge area.

Visualization

Traditionally, visualization has played an important role in the construction domain. Beginning with the primitive act of drawing on stone walls in ancient Greece, visualization techniques have evolved to a new era of information technology in the past decade. Although the benefits of visualization have been well acknowledged, the actual implementation of visualization techniques in construction has been comparatively slow, with the extent of adoption varying in different construction disciplines. Because of this discrepancy between theory and practice, identifying the most pressing challenges in visualization is critical for academia and industry to understand the actual benefits and future direction of visualization adoption in the construction field. Fig. 4 summarizes the relative importance of the six grand challenges in visualization. Overall, "output formats and mediums suited for construction" was considered the most challenging factor (3.58), followed by "budget (e.g., software license, hardware)" (3.43) and "real-time remote site modeling" (3.08). In addition, "disconnect between state-of-the-art and state-of-the-practice" (2.75), "processes for supporting decision making" (2.60), and "timely as-built modeling for decision support" (2.58) hold the last three places in this ranking with smaller margins. The following sections further analyze and discuss the ranking results from the perspectives of both academia and industry.

Output Formats and Mediums Suited for Construction

Both academia and industry respondents considered "output formats and mediums suited for construction" as the biggest challenge (3.58) in visualization adoption. This challenge ranked the first (3.57) in academic feedback and the second (3.58) in industrial feedback. The output format and medium of visualization data have to be customized to fit existing data formats in different disciplines or stakeholders. For example, clients care about interior design and the visual impression of the facility's exterior. The most suitable format and medium will be 3D rendering, virtual walk through, and immersive virtual reality experience. In contrast, schedulers and procurement managers need to know the quantitative construction work progress, such as the quantity of materials in stock, to make decisions about scheduling and procurement. Golparvar-Fard et al. (2013) identified four current challenges in visualization output format and medium, including (1) managing 3D BIM on interoperable protocols to support queries in multiple/individual

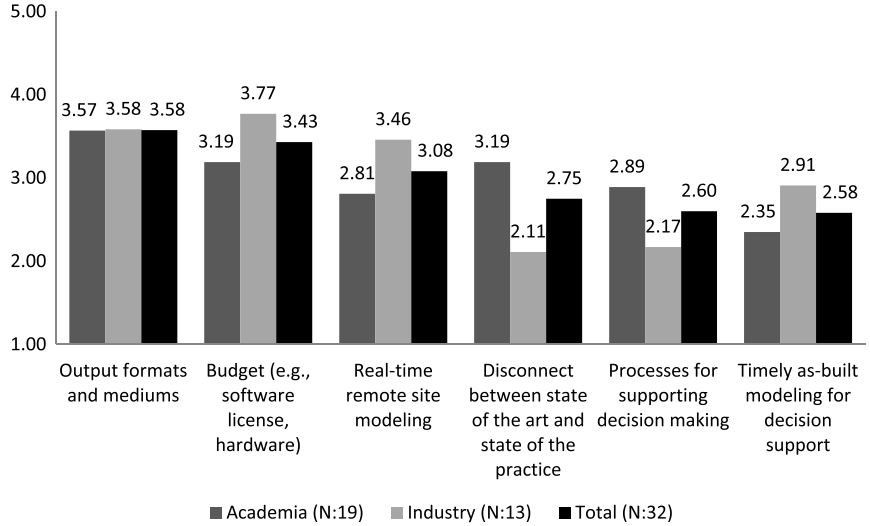

Fig. 4. Relative importance (1–5) of six grand challenges in visualization

models; (2) visualizing semantic models using web-based interfaces accessible on mobile devices; (3) enabling multiple-use real-time environments in which users can combine partial BIMs, linking BIM to GIS, and sharing with cloud-based tools; and (4) identifying quantitative methods to measure the efficiency of visualization. Addressing these challenges through the collaboration of academia and industry with shared perspectives will help in understanding the most suitable format and medium for each discipline.

Budget

Survey respondents considered "budget (e.g., software license, hardware)" as the second greatest challenge (3.43) in the adoption of visualization. From the individual perspectives of academia and industry, industry prioritized it as the most challenging factor (3.77), whereas academia ranked it the second-most challenging (3.19). This indicates a primary concern about cost and budget, which is fairly reasonable considering that profitability is the driving force in business. In general, the expense of visualization tools can be categorized into software cost, hardware cost, and operation cost. Software cost includes the purchase of computer programs or services in modeling, scheduling, 4D simulation, and BIM coordination. Hardware cost often involves the purchase of laser scanners or cameras for data collection, and workstation and mobile devices for data processing and sharing. Operation cost usually involves hiring dedicated personnel for data collection, processing, and sharing, and the maintenance and necessary upgrade of hardware and software. Training costs are usually included in the purchase of hardware and software. To set up the entire visualization system in an enterprise, initial expenses are normally high. Despite considerable initial costs for visualization hardware and software procurement, the savings in term of less future spending and project completion time remain substantial. Considering this as a one-time investment designed for long-term use, the return of investment in the long run will generate more benefits that exceed the investment (Stowe et al. 2015). For example, the potential savings to a company that invests in BIM, laser scanning, and other visualization hardware and software can be estimated based on the measurable cost savings through reduced schedule overruns, fewer requests for information, and fewer change orders (Giel and Issa 2013). In organizations in which visualization tools are available, industry experts identified "lack of training" instead of "budget" as the greatest barrier to the adoption of visualization techniques. This indicates that the operation cost of visualization techniques is comparatively less concerning to such organizations than their initial expenses.

Real-Time Remote Site Modeling

"Real-time remote site modeling" was ranked as the third biggest challenge overall (3.08), being the third challenging factor for industry (3.46), and the fourth for academia (2.81). For years, academia has been exploring the benefits of remote site modeling to advance construction visualization. It has been well acknowledged that remote site modeling will be, if it is not already, one of the major data sources for supporting construction decision making. Toward this direction, much effort has been invested in implementing existing real-time remote site modeling technologies in the construction practices (Tang et al. 2010a; Bosche et al. 2014). For instance, 3D point clouds produced by laser scanners and other data acquisition techniques such as photogrammetry have been widely used for generating as-built information for remote site modeling applications such as quality assessment (Bosche et al. 2009), progress tracking (Turkan et al. 2012), thermal visualization for energy analysis (Cho and Gai 2014), or hazard recognition (Fekete et al. 2010). In this regard, technological advances in geometric data collection have greatly increased data collection efficiency. In the past several decades, the scanning time for laser scanners has been reduced from hours to minutes, whereas the scanning range has increased from less than 50 m to several hundred meters while improving measurement accuracy. In addition, traditional data collection that requires sending personnel to the field for equipment setup and survey can be time-consuming, error-prone, and dangerous. Taking advantage of robotics, humans can be replaced by terrestrial or airborne robots (Cho et al. 2011; Huber 2014) for rapid and hazard-free data collection. Along with the development of remote data collection technology, modeling techniques have evolved from manual to semi-automated or automated processes that amplify the use of collected data such as automatic object recognition (Gai et al. 2012), surface modeling (Wang and Cho 2015), and Scan to BIM (Hajian and Becerik-Gerber 2010). Among them, Scan to BIM draws particular attention in the survey to the fact that 77% of the respondents envisioned the need for a Scan-to-BIM data standard in the near future. Such automated data processing enables real-time or near-real-time data analysis

and visualization of dynamic workspace with materials and equipment (Cho and Gai 2014; Wang and Cho 2015).

However, it is still challenging to efficiently process a massive amount of data collected from various sources on construction sites (Cho et al. 2012). More difficult challenges that researchers are facing include how to collect the data necessary for accurate and complete diagnostics (e.g., avoiding obstacles) in real or near-real time, and how to assure the quality of the collected data, which directly affects the reliability of the processed results (e.g., as-is geometric dimensions). Thus, one possible direction for future research is to focus on the accuracy, quickness, and quality of automated data collection methods and relevant strategies for processing collected data.

Disconnect between State-of-the-Art and State-of-the-Practice

"Disconnect between state-of-the-art and state-of-the-practice" was listed by academia as the second-most important challenge (3.19) in visualization. However, the industry experts showed disagreement by placing it as the least-important challenge (2.11). This discrepancy between academics and practitioners may indicate a lack of understanding of the state-of-the-art and state-of-the-practice from both sides. It further shows the importance of enhancing communication and collaboration between both sides.

Still, one positive aspect remains in that research trends and investment in many fields follow industry demands very closely. Within the industry, current practices in project scheduling and construction progress monitoring rely heavily on visualization. Survey results indicate that current uses of visualization representations in the construction projects are schedule (85%) and as-built view (62%), followed by change view (39%), physical (element /location) view (39%), product quantity (39%), process view (31%), quality view (31%), and resource use (31%). To satisfy industrial research demands, investigations in academia have worked extensively on technologies that can assist in scheduling and progress monitoring. For example, technologies such as laser scanning (Turkan et al. 2012), time-lapse photography (Golparvar-Fard et al. 2009b), and photogrammetry (Dai and Lu 2010; Bhatla et al. 2012) have been explored so that the as-built progress data are collected and then merged to form a complete as-built model, to detect progress deviations by comparing it with as-designed BIM and schedule (Kim et al. 2013). A timely understanding of industrial interests in VIMS applications can thus guide the academic community toward value-adding research directions that can eventually fill the gap between state-of-the-art and state-of-the-practice.

Processes for Supporting Decision Making

"Processes for supporting decision making" was recognized as the fourth (2.89) for academia and the fifth (2.17) important challenge for industry. Although this challenge was indicated to be less important than others, it should not be overlooked as far as further wide adoption of visualization is concerned. Because massive amounts of data are desired for the comprehensive and timely visualization of dynamic project situations, effective but rapid and concise representation with the most appropriate format(s) needs to be considered as an important future research to support decision making. This importance is supported by statistics showing that required time by users (68%) and user friendliness (63%) were recognized as the major criteria in evaluating the practicality of visualization tools.

Timely As-Built Modeling for Decision Support

Academia considered "timely as-built modeling for decision support" as the least challenging task (2.35) for visualization. However, industry practitioners ranked it the fourth most-challenging factor (2.91). Despite the fact that other practical challenges (e.g., budget) were identified as more critical, the industry also considered "as-built modeling problems that integrate the ideal world of design and imperfectness of real world" as the most important reason (62%) for why the challenges in visualization have not been solved yet. The contrast in opinions between academia and industry might result from a lack of connection between the state-of-the-art and the state-of-the-practice in the area of as-built modeling. To remedy this situation, as-built modeling, which has become a research hotspot in academia in recent years, has made rapid progress in advancing as-built data collection technologies and processing algorithms to create as-built models. However, only a few pilot tests were conducted in the field, and full-scale implementations still have a long way to go. Additionally, the data collection process remains both labor-intensive and time-consuming, and processing massive amounts of as-built data is computationally heavy as well (Golparvar-Fard et al. 2013). As mentioned previously, research efforts need to focus on expediting the data collection process and replacing the field crew through the use of automated robots and unmanned aerial vehicles (UAV) (Huber 2014). In the future, researchers can develop additional algorithms such as machine learning for effective as-built data processing (Son et al. 2012).

Information Modeling

Information modeling encourages the collaboration of all stakeholders on a project by sharing project information in a virtual model. This process is expected to reduce fragmentation in the construction industry and improve overall project performance. However, potential challenges should be fully understood before implementing advanced information modeling. Fig. 5 summarizes the relative importance of the five challenges from survey responses. Overall, "data format and interoperability" (3.14) was answered as the most-challenging factor, followed by "big data sources" (3.11), "modeling for stakeholders across the project lifecycle" (3.03), and "modeling expected facility/infrastructure behavior" (3.00). "Formalizing as-built data" (2.73) was identified as less challenging, but the ranks of the five challenges are relatively similar. In other words, all of the challenges identified were considered as important for both industry and the academy. Each of the aforementioned information modeling challenges is discussed subsequently.

Data Format and Interoperability to Enable Data Sharing

"Data format and interoperability" was considered the most important challenge. This challenge was ranked as second (3.30) by academics and third (2.94) by industry representatives. In the survey, industry practitioners indicated that information interoperability hindered their work processes somewhat (65%) or very much (29%). Examples of these barriers include BIMs in nonindustry standard formats that have to be exchanged using Industry Foundation Classes (IFC), incompatible file types, and lost model data between software applications, especially when using unstructured data formats such as images or point cloud (50%), as-built models (30%), and as-designed models (10%).

Information interoperability is considered as a dominating factor for project success in the construction industry with regard to cost and time. According to the 2004 National Institute of Standards and Technology (NIST) study (Gallaher et al. 2004), the U.S. capital facility industry loses approximately $15.8 billion dollars as a result of interoperability issues between design, engineering, construction management, and business process software systems. The BIM standards community has thus continued to actively pursue interoperability issues since 2004. For example, the buildingSMART alliance IFC schema has been revised (2×4) for better interoperability. Other data formats and standards such

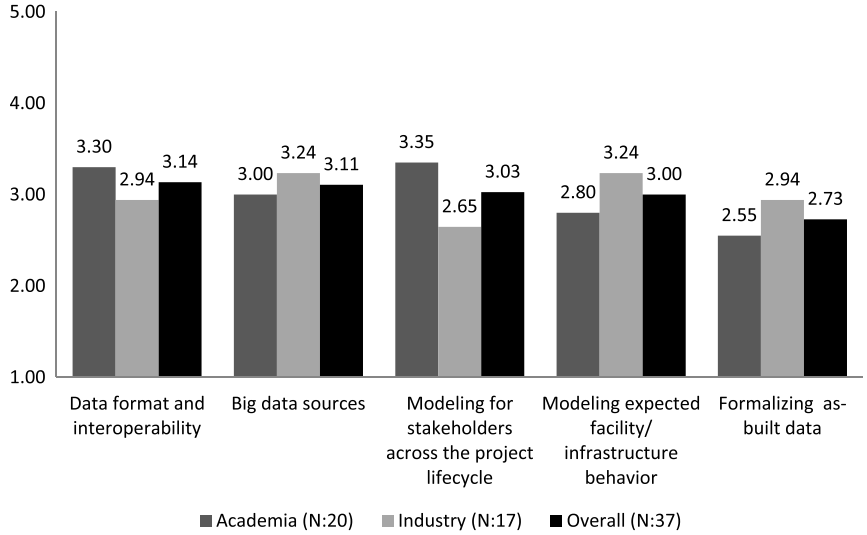

Fig. 5. Relative importance (1–5) of five grand challenges in information modeling

as Green Building XML (gbXML) (gbXML 2013) and Building Automation Modeling information exchange (BAMie) (East 2013b) have been developed to promote seamless information exchange.

Despite these efforts, there are still substantial challenges ahead in the way of adoption and quality control for data format and standard. With regard to adoption, BIM standards have surpassed the scope of information typically delivered in CAD/BIM. For example, the information that the BAMie specifies (e.g., information on facility automation system connections and their network addresses) is far beyond the scope of the current tools that deliver IFC files. Such forward-thinking data standards are presented at the risk of becoming obscure before tool vendors and users are ready to use them, and ultimately, all standardization efforts are conducted at the risk of obscurity. For BIM standards, minimizing this risk is especially challenging because of the multifaceted nature of the capital facility industry (i.e., target adopters) and its stakeholders.

With regard to quality control, the ultimate goal is to empower designers and BIM authors with tools that provide warnings and errors when requirements (e.g., model view definition, business process) are violated. Although some tools provide such capabilities, the validation rules are localized to the tool. For BIM quality control to mature, standard methodologies and rule sets should be developed. The buildingSMART Alliance mvdXML standard begins to provide a standardized and structured representation for model view definition conformance rules, but detailed content rules are expressed in a format not recognized by XML parsing libraries. Thus, there are no ready-to-use validation engines that can apply these rules to an ifcXML file. The technical solution to this problem may be easy to address, but the more substantial adoption challenge remains.

Big Data Sources Shared across the Project Lifecycle

"Big data sources" was considered the second-most-important challenge overall: third (3.00) by academics and first (3.24) by industry representatives. From the survey, information modeling experts provided specific types of challenges that they face in their research or business, such as interactions with domain knowledge, various data types (e.g., text, video) and numerous processing, access to data, large point clouds, huge amounts of monitored and sensor data, and variety of formats.

Typical computer-aided design (CAD)/BIM involves relatively large files, and the corresponding CAD/BIM data schema can be vast and complex. The IFC schema defines over 700 entity types; thus, the combination of architecture, mechanical, electrical, and plumbing models for large facilities and infrastructures represents hundreds of megabytes of data (East 2013a). Loading and processing such models demands gigabytes of available memory without considering visualization. Furthermore, computational resources are required for analyzing, querying, validating, and merging model changes among multiple BIM revisions. In addition, an increasing number of stakeholders interacting with BIM are accompanied by more diverse BIM-enabled software platforms and greater demand for processing of BIM. A couple of areas in which these problems could be addressed are querying and compression.

Experimental efforts, such as BIMQL (Mazairac and Beetz 2012), are beginning to provide standard query frameworks for BIM, but these technologies are in early development and do not elegantly support complex queries. Furthermore, efficient query technology will require indexing and database modeling methods that support geometric, temporal (with respect to the project lifecycle), and domain-centric query and report requirements. Lossless compression algorithms and standard normalization methods can reduce the size of BIM and enable more efficient processing. Compressing the 3D contents of IFC models according to application profiles may be substantially more challenging, as it requires the normalization of disparate geometry representations, polygon reduction, and validation of results (to ensure an acceptable degree of spatial accuracy). The BIM community thus faces the challenge of establishing standard BIM normalization methodologies and algorithms.

Modeling for Stakeholders across the Project Lifecycle

"Modeling for stakeholders across the project lifecycle" was ranked as the third-most-challenging task overall, being the most challenging for academia (3.35), and the least challenging for industry (2.65). Besides the challenge related to model interoperability to enable data sharing during the project lifecycle, it is important to understand who will be using the model at various stages and what information each stakeholder will need/use, in addition to modeling how that facility is expected to perform. An associated challenge is the definition of the levels of detail in a model for different operational purposes (Leite et al. 2011). Therefore, research

efforts on information modeling can cover all of these issues, which can be a great challenge especially for the research community.

In this regard, two current trends in BIM include using the model in the field during construction projects, and facility operation and maintenance. In both applications, it is necessary to understand who will be using the model and for what specific purpose(s). When the facility enters its operation phase, the BIM previously used for construction, and updated to its as-built status, can be transferred to facilities management. In addition to including the physical characteristics of the facility, BIM for facilities management needs to be augmented with service, maintenance, and cost information. The model should also include information about objects within the facilities/infrastructures, such as lifts, ventilation and fire systems, and the relationship among them in a single repository. To realize the full value of BIM, data sources must become useful to applications used by a variety of facility managers and occupants (i.e., become more than resources for architecture and structural design software). Take the example of GIS, which in its early onset was a tool for primarily scientists and engineers, and now has become a ubiquitous technology in Google Maps, smartphone navigation, and social networking mashups. Realizing this level of success for BIM is a formidable challenge, because it may require successful execution of all other challenges presented.

Modeling Expected Facility/Infrastructure Behavior—Especially Occupant/User Behavior

"Modeling expected facility/infrastructure behavior" was ranked as the fourth challenging factor, coming in fourth for academia (2.80). However, industry practitioners indicated it as the first challenge (3.24) together with "big data sources" (3.24). Therefore, this challenge needs to be considered as an important research area in the future because there are many facilities that have not met their designed performance criteria. In many of these cases, owners start to question the validity of facility design. In reality, the ill consideration of occupant behavior is one of the major causes that many facilities have not met their designed performance criteria. As of now, effort is concentrated on modeling the facility and infrastructure systems and conducting simulations to predict facility performance. Modeling facility/infrastructure occupant/user behavior is an equally important aspect in facility design and planning. However, much less has been done to advance the modeling of facility/infrastructure occupant/user behavior as compared with modeling facility systems. This is further complicated by the fact that there is virtually no standard data set for facility user behaviors. Uniform facility/infrastructure occupant/user behavior is often assumed in the facility design process. Accurately modeling of facility/infrastructure occupant behavior is a challenge that demands attention from the construction industry. To address this challenge, a better scale of user behavior data (e.g., occupant's energy consumption behavior) needs to be created and modeled in different geographic zones by considering the expected facility/infrastructure behavior in the context of its intended use.

Formalizing (and Capturing) As-Built Data

"Formalizing as-built data" was ranked as the sixth-most-important challenge, coming in fifth for academia (2.55) and third for industry (2.94, together with "data format and interoperability"), but its relative importance is not much different than other challenges, especially to industry practitioners. As-built documentation is an essential set of records, consisting of construction drawings, specifications, and equipment location, which are kept for facility management purposes. These documents are constantly being created and modified throughout the project lifecycle. The challenge of formalizing as-built data based on an existing data model thus arises.

As described in visualization challenges for timely as-built modeling, technological advancements have made it possible to generate 3D models to assess as-built conditions for construction monitoring purposes, such as verifying conformance to baseline project schedules and contract specifications. As mentioned previously, such advancements include laser or image-based 3D imaging technologies. The data captured by laser scanning or photogrammetric methods typically include a large number of point clouds and photo data. Therefore, the battlefront of formalizing as-built data is in generating as-built models in a quick and cost-effective manner (Brilakis et al. 2010; Tang et al. 2010b; Bhatla et al. 2012). In other words, derivation of as-built models such as BIM out of these raw data is often a complicated and labor-intensive process by requiring expensive and large-scale matrix manipulation and computation, which used to be only possible with supercomputers but now is in the grasp of personal computers. The cost of data modeling is often more expensive than the cost of field 3D data collection. It is rather ironic that we are getting increasingly better at discretizing the world using technologies, but are significantly lagging behind in assembling a discretized world into a holistic one. As a result, formalizing as-built data based on an existing data model presents a great challenge to the civil and construction community.

Simulation

Simulation modeling facilitates analyzing problems that are characterized by uncertainty and helps stakeholders to find integrated solutions to complex problems (AbouRizk 2010). However, there are potential challenges that may hinder the process of simulation design and implementation if not fully understood and studied. Fig. 6 summarizes six simulation challenges and their relative importance using five-point scales from the survey. Overall, "integration into school curricula" (3.62) was identified as the most challenging factor, followed by "limited multidisciplinary skills and research cooperation" (3.37), "verification and validation of output" (2.85), "incorporation of human/occupant behavior" (2.78), "credibility and adoption by industry practitioners" (2.72), and "generating models that adapt to real-world changes" (2.66).

Integration into School Curricula to Educate Future Engineers

"Integration into school curricula" was considered as the most important challenge from the survey. This challenge was ranked first from both academic and industry by 3.45 and 3.88 of relative importance scores, respectively. As shown in this survey result, lack of education and training persist as major challenges to adopting simulation by the construction industry. Construction-site stakeholders are usually not familiar with different simulation paradigms and software packages, and they have limited knowledge about how to effectively use them for different analysis and decision making on the jobsite. Therefore, the integration of simulation knowledge into school curricula is the most effective way to train future industry simulation experts and advance the simulation adoption in construction practice. This implementation will greatly contribute to students' learning in modeling real-world problems and experimenting with what-if scenarios. Students' better understating of simulation can also reinforce transparency of the simulation structures so that the model is more understandable by the users (e.g., industry practitioners). This can ultimately contribute to the wider adoption of simulation techniques in the construction industry.

Limited Multidisciplinary Skills and Research Cooperation

"Limited multidisciplinary skills and research cooperation" was considered as the second-most-important challenge overall, first

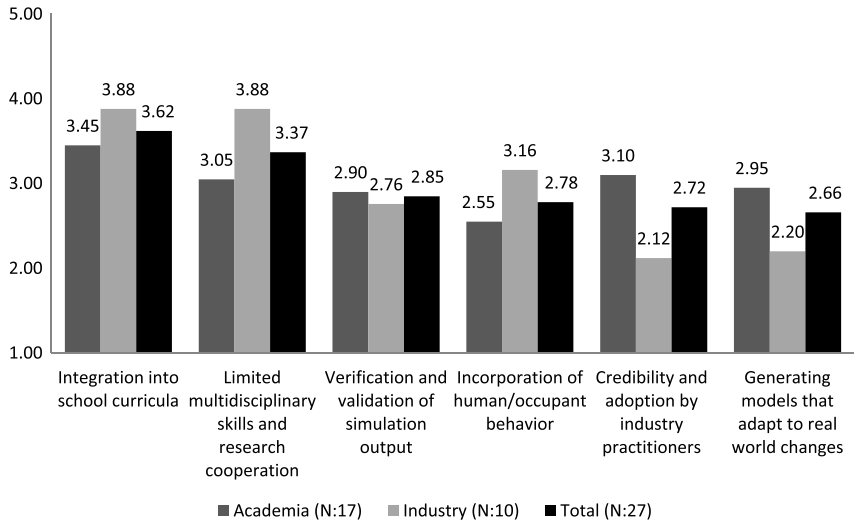

Fig. 6. Relative importance (1–5) of six grand challenges in simulation modeling

(3.88) by industry (together with "integration into school curricula") and second (3.05) by academia. In the survey, 88% of respondents stated that simulation will be a value-adding research direction within the next decade. This expectation is the result of the capabilities of simulation, including exploration of a project before actually building/creating/realizing it, theory development and experimentation under the limitations in conducting real-world experiments, and the assistance of proactive decision making. Because of these capabilities, simulation has been widely adopted in industrial and manufacturing engineering to study material handling (e.g., minimizing delays), public systems (e.g., health care and military), and service system applications (e.g., computer and communication) (Banks 1998, 2005). With the advancement of computer simulation modeling, data-driven approaches, and automated applications, effective adoption of simulation modeling techniques for complex problems requires multidisciplinary knowledge and skills in areas such as industrial and manufacturing engineering, computer science, and construction management.

Recent research studies conducted by various academic groups within construction leveraged the state-of-the-art across many different fields to design and develop simulation models that integrate multiple modeling approaches suitable for diverse components and research disciplines, and have wider ranges of applications. Examples of such efforts include data-driven and knowledge-based simulation frameworks (Akhavian and Behzadan 2013b), online simulation systems (Kamat et al. 2013), and large-scale distributed and interactive simulation (Lee et al. 2009; AbouRizk 2010; Alvanchi et al. 2011). However, simulation-modeling literature still lacks collaborative studies conducted by people from different backgrounds and research interests. In this regard, the technical advancement can help to promote interdisciplinary simulation research collaboration. For example, computer visualization methods can be useful to overcome difficulties faced by stakeholders in interpreting model outputs (Zhang et al. 2012). Moreover, the high-level architecture (HLA) (IEEE standard 1516) that provides interoperability and reusability among different simulations for distributed simulation environments can enhance the use of simulation techniques in interdisciplinary research by integrating and interacting diverse simulation components developed by different stakeholders or disciplines (AbouRizk 2010; Alvanchi et al. 2011; Menassa et al. 2014).

Verification and Validation of Simulation Output

"Verification and validation of output" was ranked as the third-most challenging overall, being the fourth challenging for both academia (2.90) and industry (2.76). Verification is concerned with building the model right, whereas validation is concerned with building the right model (Banks 2005). Verification is often necessary to avoid modeling mistakes and to make sure that the model is implemented correctly in the simulation software. In validation, the modeler tries to confirm that the model is an accurate representation of the real world or imaginary system. In construction, however, typical simulation modelers are not the project stakeholders and subject matter experts who make the decisions. Therefore, it is very important that the model is clearly explained to the decision makers who can make comments and modifications for model validation. This is considered one of the biggest challenges in deploying simulation for construction applications. In this regard, animation and visualization are viewed as great interfaces for communicating the output of the simulation with the stakeholders. A 3D visualized simulation model can also present volumes of data in a manner of seconds that can otherwise take hours to review (Kamat and Martinez 2003; Zhang et al. 2010).

In construction simulation, often an imaginary system is modeled and studied to be built, meaning that the systems being modeled often do not exist (Martinez 2009). This is why the result of the simulation model should be compared with the historical information from a situation "close enough" to the intended use, or checked by subject matter experts. However, model validation in the construction industry is particularly difficult, given that each project is unique and, hence, may be difficult to generalize. In this case, full documentation and reporting of simulation case studies can make up for this weakness by providing data sets for the validation of new models. In addition, many of the challenges in the area of verification and validation of construction simulation models can be potentially alleviated through leveraging data collection and analysis techniques (Akhavian and Behzadan 2011). In particular, recent advances in data sensing and mining techniques can be used to improve/enhance the validation process by capturing massive raw data from site and then interpreting them, in addition to converting them into input or output data (Ahn and Lee 2015).

Incorporation of Human/Occupant Behavior into Simulation Models

"Incorporation of human/occupant behavior" was ranked as the fourth-most-challenging task overall, being the third challenging for industry (3.16). Despite academia's ranking of this task as "least important" (2.55), this challenge needs to be considered as an important future research agenda, given the high demand in the labor-intensive construction industry. One of the most commonly used simulation paradigms that incorporates human/occupant behavior is agent-based simulation (ABS), which is "a promising strategy for understanding behavior-based problems in construction" (Walsh and Sawhney 2004). In ABS, simultaneous actions of various autonomous individuals or agents in a system are modeled (Bonabeau 2002). ABS is still a challenging field of research and practice in construction, because of the complexity and variety of the agents (i.e., stakeholders and labors) involved in construction projects. Despite the advantages of ABS in human/occupant behavior analysis, academia and industry practitioners in construction domains indicated several key challenges associated with this simulation paradigm throughout the survey, such as lack of fundamental knowledge of human behaviors, determining the right modeling purposes and details, incorporating behavioral aspects of decision making, and empirical validations. In this regard, future interdisciplinary research efforts between the social science domain and the construction domain can enable more reliable human/occupant behavior modeling and analysis, such as construction worker behavior (Ahn et al. 2014) and occupants' energy consumption (Anderson et al. 2014)

In addition, one of the recent trends in incorporating human behavior and activity data is using ubiquitous sensing devices. Smartphones equipped with a variety of on-board sensors are nowadays used by most of the population; nearly two-thirds of people in the United States (64%) own smartphones based on the data collected in 2014, up from 35% in 2011 (Pew Research Center 2015). Their small size, affordability, and computing and transmission capabilities make smartphones ideal platforms for human activity recognition for many different applications such as health care and transportation (Brezmes et al. 2009; Wang et al. 2010). Recently, research studies have been conducted within the construction domain to evaluate the feasibility and applicability of using smartphone sensors for construction work (Ahn et al. 2013; Akhavian and Behzadan 2015). Not only does ABS benefit from data pertinent to human behavior and activity, but such data can also be incorporated into other simulation paradigms as well. However, privacy remains a major challenge in incorporating human subject data such as position and body motions.

Operations-level simulation in construction is not possible without modeling human actions and behaviors. Therefore, realistic simulation models require collecting data one way or the other from project personnel. Such data collection can be conducted using manual and offline methods, such as interviews and surveys in which people have the right to control the information they share (Martinez 2009). In contrast, automated data collection methodologies, such as those used in data-driven simulation, deploy pervasive sensing devices including vision-based (e.g., cameras) (Golparvar-Fard et al. 2009a; Han et al. 2014a; Seo et al. 2015) and non-vision-based (e.g., position sensors) data acquisition infrastructure (Teizer et al. 2008) in cases in which people are more concerned about their privacy.

Credibility and Adoption by Industry Practitioners for Decision Making

"Credibility and adoption by industry practitioners" was ranked as the fifth-most-challenging factor. However, the knowledge gap between academia and industry still exists with regard to this challenge, as evidenced by the discrepancy in ranking: third-most important for academia (3.10) and sixth for industry (2.12). Wide accreditation and adoption, coupled with the practical implementation of simulation techniques, in construction have always been considered a major gap between academia and the industry. The lack of trust by industry practitioners toward the effectiveness of using simulation models in their projects has to some extent prohibited the widespread use of simulation in practice. AbouRizk (2010) indicated that such trust would be developed only when the collaborations take place over a long period of time with successful examples of simulation systems resulted from industrial involvement and steering (Hajjar and AbouRizk 1999). Therefore, the adoption of and investments in simulation by industry practitioners can lead to a two-way relationship for great achievements in academia that eventually turns into practical implementations by industry partners. One major encouraging factor that will help gain credibility and trust for the use of simulation by industry is leveraging reliable contextual input information to build simulation models. This practice is currently pursued in the academic research community, to design and develop more realistic and subsequently reliable simulation models (Lee et al. 2009; Akhavian and Behzadan 2013a).

Meanwhile, the industry's reluctance to employ simulation for decision making may be the result of reasons other than the mere lack of trust in its effectiveness. Simulation is a technical field that needs an expert modeler to create the model, modify it for verification and validation, perform sensitivity analysis, and interpret the results. Finding and recruiting modelers with a diverse background that facilitates the understanding of construction practices in addition to simulation modeling is not an easy task. However, a user-friendly software design with sufficient guidelines and minimal training would facilitate the practical implementation of simulation modeling on jobsites.

Generating Models That Adapt to Real-World Changes

"Generating models that adapt to real-world changes" was ranked as the least challenging, coming in fifth for both academia (2.95) and industry (2.20). Despite this ranking, this result may be because of the industrial use of traditional static simulation systems in current practice; realistic simulation models need to keep up with the changes occurring on the jobsites when considering the dynamic and complex nature of construction projects. Most simulation models are created during the preconstruction phase, in which engineering assumptions about the availability of tools, resources, information, materials, equipment, construction methods, and flow of activities form the basis of the simulation input (Gao et al. 2013). However, the dynamics involved in the projects make it necessary to have adaptive simulation models that change based on the modifications made to initial project plans and decisions (Lee et al. 2013). Occasional updating of simulation models according to changes captured manually by decision makers is one way to keep the model up to date.

With the advancement of information technology and sensing instrumentations, the creation of automated data-driven simulation models that adapt to dynamics of the projects has opened new horizons in construction simulation research. With an emerging multidisciplinary field of research, major progress has been made in academia toward the design and prototyping of such dynamic simulation frameworks. Despite this progress, the industry is still inclined toward using traditional static simulation systems (Lee et al. 2013). Such static models often fail to capture the dynamics of the field operations, and thus soon become obsolete (AbouRizk 2010). In the survey, industry practitioners stated that simulation models

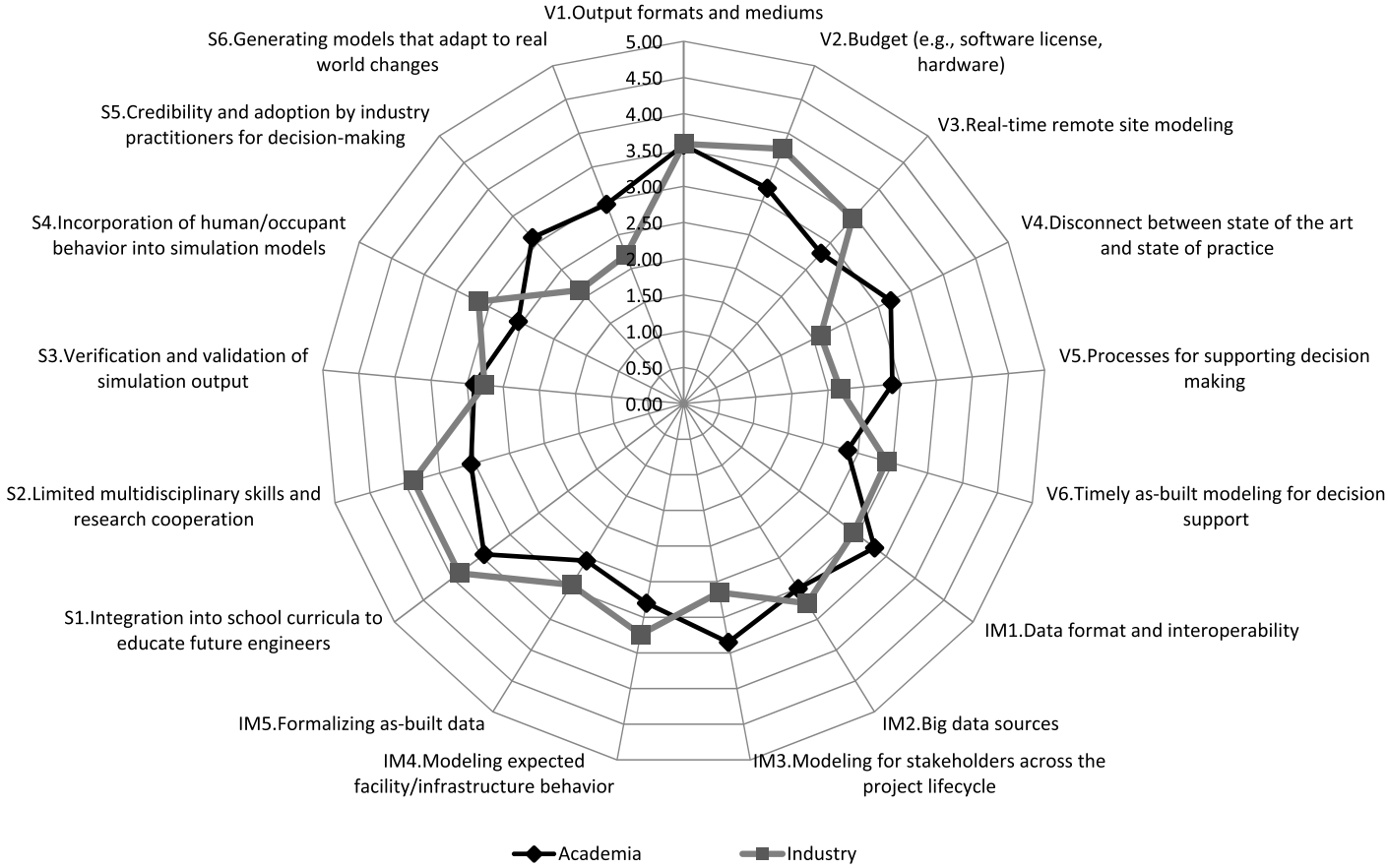

Fig. 7. Relative ratings of 17 grand challenges in VIMS

used in their projects are not fully dynamic (i.e., do not get updated), which may result in outputs that may not be realistic. Discrepancies between the output of such simulation models and real-world system measures are a major roadblock in the adoption of simulation models for decision making in the industry.

Generating adaptive simulation models on the basis of factual data collected from jobsites requires advanced data analysis. Heterogeneous and asynchronous construction data collected from different sources need to be fused and synchronized (Shahandashti et al. 2011). Moreover, customized data mining and analytics techniques should be developed to enable pertinent knowledge extraction (Soibelman and Kim 2002). This introduces another challenge in generating dynamic simulation models that depend on automated data collection systems from equipment and workers. Another challenge brought up by some experts is that data collection procedure may hinder tasks performed by the equipment and their operators. To overcome this issue, the use of nonintrusive sensing techniques (e.g., wireless and wearable sensors) can be one of the future research areas.

Summary

Fig. 7 describes the relative importance of all 17 challenges in the VIMS knowledge area that are generated from a survey among academia and industry practitioners. Identified challenges include both technical challenges (i.e., V1, V3, V6, IM1, IM2, IM4, IM5, S3, S4, and S6) and adoption challenges (i.e., V2, V4, V5, IM3, S1, S2, and S5). Specifically, technical challenges involve data format and interoperability issues, as-built data and modeling, model verification and validation, and real-time modeling during the project lifecycle, in addition to human behavior modeling focusing on the users and occupants, whereas adoption challenges are associated with sociological/cultural/organizational issues such as budget, creditability, decision support process, and/or education and research cooperation issues. Survey results demonstrate the importance of considering both technical and adoption challenges by showing that these challenges are both technical and sociological/cultural/organizational (74%) in nature rather than purely technical (8%) or purely sociological/cultural/organizational (18%). However, it is very likely that industry practitioners place more emphasis on adoption issues (e.g., budget, research cooperation, education, and training for industry VIMS experts), as shown in V2, S1, and S2 in Fig. 7. In the survey results, 35% of industry respondents indicated more importance of adoption issues than technical issues, whereas only 5% of academia respondents did. In contrast, academia synthetically situates their concerns on both technical and adoption issues. They also feel a burden of actual implementation and decision support of VIMS in the real world, such as V4, V5, IM3, S5, and S6 in Fig. 7.

To statistically test the difference of perspectives in VIMS challenges between academia and industry, an independent sample t-test was conducted for each challenge. There was a significant difference between academia $[M = 3.19$, standard deviation $(\mathrm{SD}) = 1.18]$ and industry $(M = 2.11,\ \mathrm{SD} = 0.97)$ regarding V4 (i.e., disconnect between state-of-the-art and state-of-the-practice); $t(30) = 2.64$, $p = 0.01$, although the test results for others do not show significant differences of perspectives between them. This knowledge gap of disconnection between

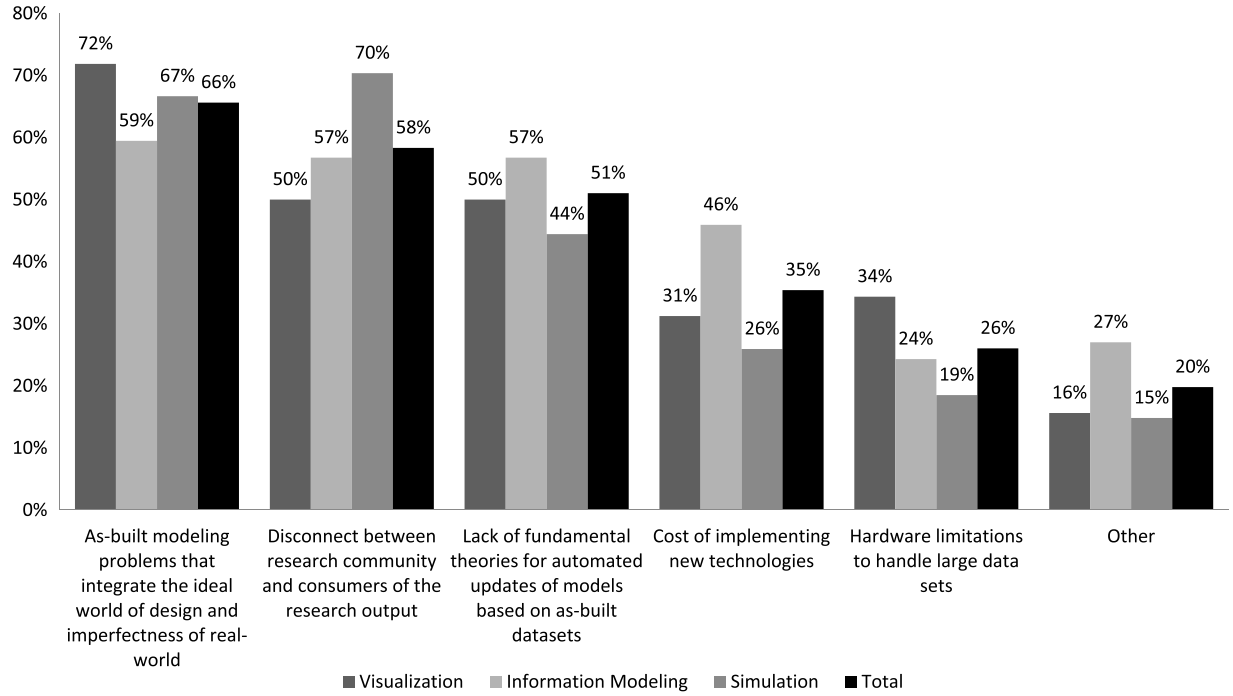

Fig. 8. Summary of why VIMS challenges have not yet been solved

state-of-the-art and state-of-the-practice between academia and industry can be a result of lacking communication and collaboration between both sides.

However, shared perspectives between academia and industry have increased through collaborative research efforts. For example, information modeling techniques such as BIM have been widely applied to construction fields by reducing knowledge gaps in the information modeling area (Wang and Leite 2015) and indicating shared future challenges between academia and industry, such as data format and interoperability, in addition to big data processing, as shown in IM1 and IM2 in Fig. 7. This implies that the increased application of VIMS can reduce knowledge gaps between academia and industry with cooperation and communication, and eventually can solve these challenges for the construction industry by reliably modeling, representing, and interpreting huge amounts of data and variety of format, and then using them in decision making in a quick and cost-effective manner. Specifically, advanced and automated technologies for data sensing/collection and processing of a massive amount of data can help to solve many practical problems, such as as-built modeling or human behavior modeling, in which industrial practitioners have their interest as shown in V3, V6, IM4, and S4 in Fig. 7. Furthermore, the advancement of each knowledge area of VIMS mutually supplements to overcome challenges in each area (e.g., effective visualization representation viewed as great interfaces for communicating and validating simulation output to widely adopt simulation models to practical problems in the construction industry).

Future Directions

In the past few decades, VIMS techniques have changed rapidly and dramatically the way many construction processes are executed. As a result of these advances, there has been an increase of interest in VIMS. Specifically, visualization techniques can make it easier to identify spatial and temporal conflicts, monitor construction progress, and control construction quality. Information modeling is an extension of old principles of collaboration among project participants by placing a great emphasis on the huge amount of information that is not limited to conventional drawings, but shared to maximize project performance. In addition, simulation modeling can facilitate the planning, control, and operation of construction projects as a decision support tool. According to these potentials, the future of VIMS is exciting but still challenging. Indeed, most organizations continue to face serious challenges with VIMS. The most salient challenges include an overload of data and information, transforming raw data into contextual knowledge that describe the dynamics of the real world system, and complex geometries with occlusions and complex shapes. Among them, transforming raw data into contextual knowledge [77% in visualization (V), 53% in information modeling (IM), 60% in simulation (S)] was recognized in the survey as the most challenging factor, followed by an overload of data and information (8% in V, 29% in IM, 0% of S), complex geometries (8% in V, 6% in IM, 40% of S). In addition, industry experts were asked to identify bottlenecks of information modeling in practice. The findings recognize software limitations (69% in V, 65% in IM, 70% in S) as a critical barrier, versus hardware limitations (6% in V, 6% in IM, 10% in S). In addition, a respondent added that lack of education and training is also a current bottleneck.

Similar questions were asked to both industry and academia to gauge their thoughts on why these challenges are yet to be overcome, as shown in Fig. 8. Survey participants from both academia and industry in each VIMS knowledge area commonly considered as-built modeling problems (66%), disconnect between the research community and consumers of the research output (58%), and lack of fundamental theories for automated updates of models (51%) as the critical causes. These results confirm previously discussed challenges in VIMS, such as data collection/processing of large amount data for assisting rapid decision making and collaboration between academia and industry. Specifically, as-built and real-time modeling can be valuable research directions in academia.

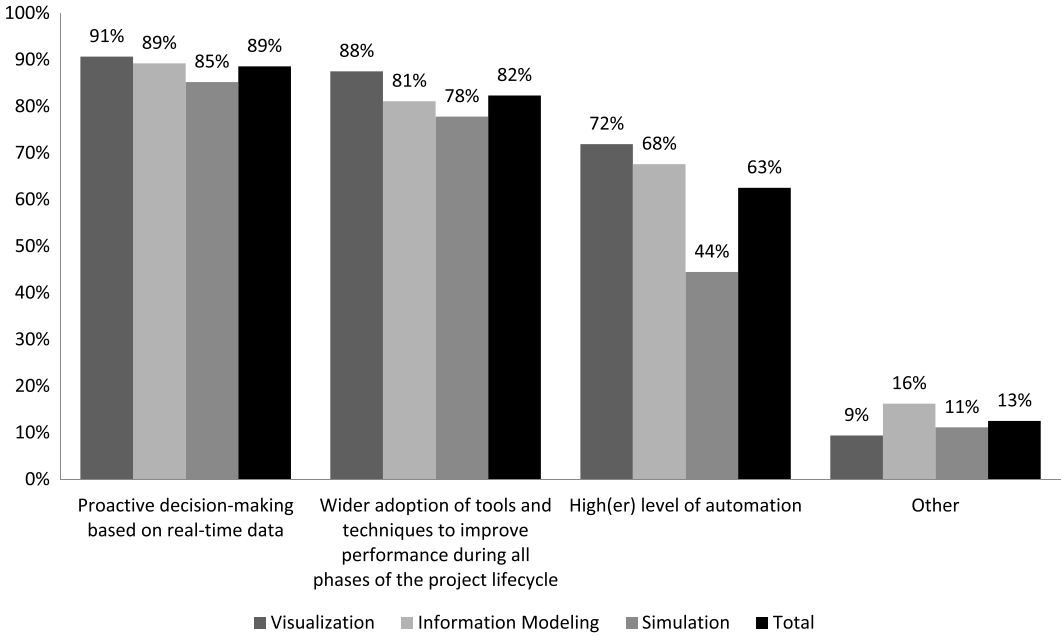

Fig. 9. Summary of expected effects if VIMS challenges are solved

As shown in Fig. 7, industrial practitioners recognized as-built and real-time modeling as the most critical technical challenges of VIMS (i.e., V3, V6, and IM5), because it can enhance timely and appropriate decision supports under complex and changing large capital project environments. In this regard, the application of advanced sensing (e.g., mobile robots and sensors, UAV) and information processing (e.g., signal processing such as IMU data, 3D image processing, natural language processing) enables advanced as-built and real-time modeling. These are currently ongoing research areas in academia. Further, interactive systems that integrate VIMS (e.g., HLA distributed simulation architecture that incorporates sensing and visualization), in which data sensing/collection, data modeling, simulation, and visualization modules are seamlessly interoperable with the standardized data format, can reinforce the ability of VIMS in rapid and reliable decision supports and satisfy industrial needs for VIMS in large-scale capital projects and facility/infrastructure managements.

In contrast, although academia believed that the cost of implementing new technology is a less important reason (23%) to avoid implementation, the industry recognized cost as one of the main barriers (54%). Some respondents also argued that characteristics of the construction industry, such as low profit margin and low short-term return, contribute to the slow adoption of VIMS techniques in construction processes. Therefore, industry involvement into VIMS research through collaborations over a long period of time can increase trust by industry practitioners toward the effectiveness of VIMS, which can eventually strengthen the industry's adoption of and investments in VIMS.

Understanding the specific origins of VIMS challenges helps in finding solutions for solving the challenges. It is also interesting to know how both the industry and academia envision the effects to be expected after solving these challenges. As shown in Fig. 9, both industry and academia recognized from the survey that proactive decision making based on real-time data (89%) is the most possible effect of solving current challenges in VIMS, followed by wider adoption of tools and techniques to improve performance during all phases of the project lifecycle (82%), and higher level of automation (63%) and others (e.g., better integration of systems, disciplines, and analysis; better predictability; less time spent looking for latest specific project information; and a cultural shift). One notable point in other opinions is that solutions of these challenges in VIMS will lead to a cultural shift in both management and workforce. This cultural shift will give regulatory authorities greater confidence in the utility of VIMS tools, which will in turn advance the adoption of VIMS techniques in construction processes.

Closing Remarks

This paper identified and analyzed grand challenges in visualization, information modeling, and simulation for the construction industry. Seventeen grand challenges (i.e., six for visualization, five for information modeling, and six for simulation) were preliminarily identified by the ASCE VIMS committee. From an expert survey on both academia and industry, the identified VIMS challenges were validated and the relative importance of the identified challenges was further examined in addition to an in-depth investigation of current practices and future directions. Despite a few knowledge gaps regarding VIMS challenges between academia and industry, shared views on VIMS challenges from both academia and industry can help researchers to define their research directions, to reduce these gaps. Specifically, both technical challenges (e.g., advanced data collection and process for real-time as-built modeling) and sociological/cultural/organizational challenges (e.g., budget, education and training for VIMS experts) need to be simultaneously dealt with in the VIMS research community through the involvement of industry practitioners. Sustained discussion and cooperation to address these challenges between academia and industry will spur on the evolution of knowledge of, and the technical advancement in, a wider adoption of the VIMS for the construction industry. Furthermore, a hint from VIMS grand challenges throughout the entire project lifecycle is expected to be useful in solving potential grand challenges in other disciplines, including architecture, engineering, and facility management, to not only effectively deliver capital projects, but also to sustain resilient facilities and infrastructures.

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