CO6541

Viability of the BIM Manager Enduring as a Distinct Role: Association Rule Mining of Job Advertisements

M. Reza Hosseini[1], Igor Martek[2], Eleni Papadonikolaki[3], Moslem Sheikhkhoshkar[4], Saeed Banihashemi[5], Mehrdad Arashpour[6]

Abstract:

Building Information Modeling (BIM) has developed as the definitive technology for managing construction projects. With its rise, the corresponding role of BIM manager has emerged as a necessary adjunct role in coordinating BIM enabled projects. The ascent of the BIM manager has attracted a significant body of research investigating the various competencies and responsibilities required of the role. While BIM is here to stay, the work of Akintola et al. (2017), however, asserts that a distinct role oriented around BIM, is itself transitory. The conclusion in Akintola's work represents a significant departure from accepted assumptions on the viability of the BIM manager role. This research sets out to test the likelihood of a long-term market demand for the BIM manager, as a distinct role, based on a robust quantitative analysis of open-source data from a rich

[1] Lecturer, School of Architecture and Built Environment, Deakin University, 1 Gheringhap Street, Geelong, Victoria 3220, Australia, email: Reza.Hosseini@deakin.edu.au (Corresponding Author)
[2] Lecturer, School of Architecture and Built Environment, Deakin University, 1 Gheringhap Street, Geelong, Victoria 3220, Australia, email: Igor.Martek@deakin.edu.au
[3] Lecturer, The Bartlett School of Construction & Project Management, University College London, London, UK, email: e.papadonikolaki@ucl.ac.uk
[4] Research Assistant, Civil Engineering Department, Iran University of Science and Technology, Narmak, Tehran, Iran, email: msheikhkhoshkar@gmail.com
[5] Lecturer, Faculty of Arts and Design, University of Canberra, University Drive, Bruce, ACT 2617, Australia, email: Saeed.Banihashemi@canberra.edu.au
[6] Lecturer, School of Property, Construction and Project Management, RMIT University, Melbourne, Australia, email: mehrdad.arashpour@rmit.edu.au

empirical dataset of global relevance for the North-America, Europe and Australasia. Text mining methods are used. 199 BIM related jobs were retrieved from 14 of the most relevant job websites, representing the global English speaking jobs markets. Key knowledge, skills and abilities attributes of the BIM jobs were extracted and analyzed. Analysis reveals there is no significant difference between the roles of ‘BIM manager’ and ‘BIM coordinator.’ Moreover, the findings highlight that these two BIM roles align with that of ‘project manager.’ Most importantly, BIM roles are shown to supplement the lack of BIM expertise within the role of ‘project manager,’ and that as BIM capabilities are increasingly absorbed by project managers, the rationale for an independent BIM expert will fade. The corollary is that BIM roles are a stopgap measure that can be expected to disappear as project managers absorb requisite BIM skills. The practical implication for the construction engineering HR departments is that the prevailing policy of retaining dedicated BIM managers into the longer term should shift rather to one where project managers are re-trained to a level where they possess a comprehensive, independent BIM expertise.

Keywords: Building Information Modeling, BIM manager, project manager, text mining, association rule mining, job advertisements

Introduction

Building Information Modeling (BIM) is now ubiquitous within the construction industry (Cao et al. 2018). Reliance on BIM has brought with it a dramatic increase in demand for employees with BIM capabilities and skills (Suwal and Singh 2017; Zhang et al. 2018). Research studies confirm that the construction industry now requires its team members to be able to participate in BIM processes and utilize BIM tools (Oraee et al. 2017; Puolitaival and Forsythe 2016). Moreover, the wide and growing acceptance of BIM in the construction sector has sparked a transition from traditional roles and positions on construction projects to newly defined roles and responsibilities that are highly dependent on technology-based skillsets (Barison and Santos 2011; Wu and Issa 2013). Specifically, the recently evolved role of BIM manager (BM) has emerged to safeguard the success of BIM-enabled construction projects and facilitate BIM use (Rahman et al. 2016).

Indeed, BMs are seen as a "must have" role in BIM-based projects (Gathercole and Thurairajah 2014). The novelty of the phenomenon, however, indicates that market definitions of a BIM functional role remain fluid (Wu et al. 2017), while the continued rapid technological progression of BIM itself ensures further continuous evolution of the role (Succar et al. 2013; Suwal and Singh 2017). Thus, while BIM is now indispensable, and management of BIM processes core to construction project success, the current market practices and future trends that attend the engagement of BIM practitioners remain both crucial and unknown (Zhang et al. 2018). Identifying how the role of the BIM professional is expected to progress into the future is of strategic concern to human resources managers in the construction industry (Wu and Issa 2013).

In recognition of this, existing studies have focused on exploring the skill and competencies of BMs (Antisari 2017; Uhm et al. 2017; Wu and Issa 2013), or the functions attached to the BM

(Akintola et al. 2017; McPartland 2017). By contrast, no known studies, apart from the work by Sebastian (2011), and Akintola et al. (2017), have looked into the long-term durability of a dedicated BIM role.

Even so, these long-term investigations arrive to their conclusions based on qualitative analysis that reflects perceptions of informants, rather than on hard data. Whereas the findings have strong merit, they do warrant further research based on real-life records (Treisman 2007). In view of this, the present study is an attempt to extend the work of Akintola et al. (2017) by assessing the legitimacy of the BM role. The research accesses databases of actual BM job market records, and evaluates the roles ascribed to BMs in order to establish the duties of the role, along with the degree of divergence of the BM role from complementary roles in construction.

Background

The BIM market is projected to grow from US$3.16 billion in 2016, to US$7.64 billion in 2022. This is an annual growth rate of over 16% (MarketsandMarkets 2017). This presents the industry with challenges on multiple fronts, not the least of which being the attendant human resources task of ensuring construction firms are staffed with sufficiently capable BIM employees able to facilitate the growing number of BIM-enabled projects (Akintola et al. 2017; Sebastian 2011; Suwal and Singh 2017). There currently exists a pressing need to recruit BIM talents, assesses their competencies, and then place them into new roles and positions within the existing organizational structure (Deutsch 2011; Joseph 2011; Lewis et al. 2015; Uhm et al. 2017). Thus, it is important to identify and define the exact competencies that need to be possessed; trained in-house or brought in (Solnosky et al. 2014; Wu et al. 2017; Zhang et al. 2018). Additionally, there is a need for a proper appreciation of the exact nature of the BM role, and to demarcate it from those of other positions concurrent on BIM-enabled projects (Akintola et al. 2017; Badi and Diamantidou 2017).

BIM-related roles

BIM roles continue to evolve, consequently associated Knowledge, Skills and Abilities (KSAs) pertaining to them, have attracted a good deal of research in recent years (Aibinu and Venkatesh 2014; Wu et al. 2017). As an example, Uhm et al. (2017) defined eight BIM-related jobs comprising director, BIM project manager, BIM coordinator, BIM manager, BIM Mechanical, Electrical and Plumbing (MEP) coordinator, BIM designer, BIM architect and BIM technician. Barison and Santos (2011) classified BIM jobs into eight types. These were BIM manager, modeler, trainer, director, technician, consultant, marketing manager, and software support engineer. Apart from studies devoted to identifying the roles associated with BIM on projects, there are also several studies that investigate the competencies and skills of various BIM-related jobs. As a comprehensive reference, the Australian Construction Industry Forum (ACIF 2017) presents a framework that covers skillsets and competencies required of all the roles and responsibilities associated with BIM-enabled projects. Giel and Issa (2015), however, target their investigation on the owners, arguing that it is they who are critical to the success of BIM-enabled projects. Taking another approach, Rahman et al. (2016) compared the two roles of ‘project manager’ and ‘BIM manager,' finding that these two roles are largely coincidental in sharing by far a wide range of skills, rather than being discrete from one another. Their difference is primarily found in their name only.

The emergence of the professional BIM manager

As defined by ACIF (2017), a BIM manager is an individual responsible for the management and administration of all the processes associated with BIM on a project. This role entails organizing, planning, scheduling, directing, controlling, monitoring and evaluating BIM processes, to make sure they are aligned with the pre-defined project objectives (Deutsch 2011; Succar et al. 2013). The position of BIM manager has emerged as a BIM-specific role with the primary function being "…to manage people in the implementation and maintenance of the BIM process." (Barison and Santos 2010) According to Holzer (2015), the BM role involves developing a support infrastructure that enables others to implement BIM on BIM-enabled projects. BIM manager is the person responsible for a wide range of BIM-related tasks on projects, including providing support, instruction, and training of others in the implementation of BIM (Barison and Santos 2011). There is nevertheless a degree of uncertainty regarding the functions and duties expected of BIM managers. More pronounced and controversial, is the ambiguity regarding the overlap of duties shared between the BIM manager and those of other complementary roles (Akintola et al. 2017; Berlo and Papadonikolaki 2016; Wu et al. 2017).

In addressing the role of the BIM manager, several studies have attempted to explore BIM managers in terms of their KSAs and responsibilities, as tabulated in Table 1.

As can be gleaned from the findings of the available studies on the role of the BIM manager, the dominant theme is the discovery of competencies and responsibilities associated with the role. Two main approaches are evident; tabulation of the perceptions of industry practitioners (ACIF 2017; Holzer 2015), or analyses of documented data (Barison and Santos 2011; Uhm et al. 2017). This second approach includes studies that define necessary skills and responsibilities of BIM roles in view of the necessities for BIM implementation on projects. The work of Succar et al. (2013) stands out in this regard. It is also evident from the list in Table 1, that looking into the actual legitimacy or relevance of the BM role itself, has not been considered.

Nevertheless, a body of study, conducted by Berlo and Papadonikolaki (2016) and Papadonikolaki and Oel (2016) touch upon the potential overlap and conflict between that of the BIM manager and existing roles, but do not further delve into the implications of this overlap. Rahman et al. (2016) highlight the common ground between the BIM manager role and project management role, giving particular attention to the technical construction skills. Indeed, the only available study attempting to assess the validity of the BIM manager role against the backdrop of existing roles is the recent study by Akintola et al. (2017), who surmise that the BIM manager role in construction projects is transitory and ultimately unsustainable. While the study is unique in challenging the legitimacy of the BIM manager as a stand-alone role, the findings simply offer views of industry experts based in South Africa. The weaknesses of the above efforts thus lie in the generalizability of these findings to other contexts, particularly to countries such as the United States of America (USA), United Kingdom (UK) and Australia, where BIM has achieved greater acceptance (Gholizadeh et al. 2018). The objective of the present study is thus to test the important findings of Akintola et al. (2017) with empirical objective data drawn from a greater global context.

Theoretical foundation in 'Activity' and 'Institutional' theory

The present study borrows from the theoretical underpinning of the study by Akintola et al. (2017), which assimilates both *activity theory* (Engestrom 2000) and *institutional theory* (Tolbert and Zucker 1999) in developing a theoretical foundation to their study of the legitimacy of the BIM manager role. This convergence effectively assists in exploring the interactions between the BIM manager role and existing roles in construction projects, and explains the mechanics of creating new roles associated with implementing BIM on construction projects (Akintola et al. 2017).

With the advent of BIM, existing organizational structures and roles must co-evolve with the introduced technology by developing and supporting new roles along with the means to complete the tasks and meet objectives. Nevertheless, as an organizational system adapts to major changes by introducing new roles to deal with technological disruptions or other operational discontinuities, those roles may prove temporary as the organization absorbs the change, legitimizing and standardizing them within standard work practices (Akintola et al. 2017). That is, social actors (referred to as roles here) are able to influence others and exercise authority within an organizational structure only as long as they are able to take advantage of the scarcity of their knowledge and skills (Tyler 2006). The legitimacy of new roles within an organizational system remains unchallenged only to the extent and only as long as these roles facilitate their responsibilities and functions to deliver outcomes that cannot be covered by the original existing roles and positions (Akintola et al. 2017; Tyler 2006).

Research Methods

Methodological rationale

This study aims to offer a robust quantitative analysis by means of text mining a rich empirical dataset extracted from the real-world BM job market. It explores the viability of the BM role by direct role analysis with other related job descriptions, as opposed to inferring such based on mere qualitative evidence drawn from industry experts' perceptions. There are several ways to present a picture of the market demand for a role such as BIM manager. Among these, as pointed out by Succar et al. (2013), analyzing 'job advertisement descriptions' crafted by recruitment sites is a particularly legitimate approach. In contrast, data acquired through surveys or interviews are influenced by popular prejudices, reflecting opinion rather over objective reality (Treisman 2007). Consequently, the data used in the present study is based on real-life job advertisement descriptions for BM roles. Such data are typically retrieved in an unstructured format, calling for a method to process the natural human language used. Data mining is the approach of choice for a robust, quantitative discovery of patterns in datasets. Typical data mining techniques, however, extract information from a structured database, and are therefore limited in their ability to handle huge amounts of unstructured textual documents. Text mining is a remedial solution, able to deliver quantitative robust discovery of knowledge from collections of unstructured text (Yoon and Park 2004). In this regard, text mining was assessed to be a directly applicable tool to the task in hand (Kotu and Deshpande 2015), and is thus adopted here.

Text mining

Text mining is defined as “an attempt to separate valuable keywords from a mass of other words (or relevant documents from a sea of documents) and use them to identify meaningful patterns or make predictions” (Kotu and Deshpande 2015). This approach requires converting text into semi-structured data in the form of vectors and matrices. These are afterwards used in performing analytical techniques applicable to structured data, characteristically employing powerful algorithms (Kotu and Deshpande 2015; Miner et al. 2012). Miner et al. (2012) divided text mining into seven practice areas, based on the focus and the analytical techniques utilized within each of these areas. In view of the classification by Miner et al. (2012) along with the objectives of the study, the present study follows the analytical procedure illustrated in Figure 1; a discussion of which follows.

Information retrieval

The term “BIM Manager” is closely associated, if not synonymous with, the terms “BIM Coordinator” and “senior BIM Manager” (Berlo and Papadonikolaki 2016; Uhm et al. 2017). These were used as keywords to extract related job advertisement from major recruiting websites. The advertisements were extracted from 14 major websites, including LinkedIn, www.seek.com, www.indeed.com, www.careerbuilder.com, www.totaljobs.com. However, for data collection and analysis reasons, these were limited to advertisements in English. All the job advertisement cases were copied into a spreadsheet with the name of associated companies. The data were sorted based on the names of companies to spot and omit any duplication. As of December 2016, 199 jobs were retrieved directly seeking BMs across various countries.

When the concept of a study is clearly distinctive, such as searching for BM advertisements from a pool of other advertisements, few documents are sufficient to reveal the distinctive embedded features (Weiss 2005). Given that the total number of advertisements for BIM-related jobs is limited (Uhm et al. 2017), the sample size for BIM manager advertisements, as a subset of this pool, was deemed adequate. Subsequently, the data was recorded as a spreadsheet that contained 4 columns: ‘country’, ‘position title’, ‘responsibilities’, and referenced against required knowledge, abilities and skills (‘KSAs’). The resultant matrix was utilized as the data source for the ensuing text mining analyses. The information retrieval results are summarized in Figure 2. As illustrated in Figure 2, the largest number of advertisements came from the USA, with the UK and Australia following. This was anticipated, since these are among the countries representing the major world BIM markets (MarketsandMarkets 2017). The gap between the number of advertisement from the UK and the USA with Australia is also explicable. USA contractors are leaders in BIM implementation while an unprecedented number of UK contractors implement BIM in compliance with the announced UK government policy calling on BIM patronage (Bernstein et al. 2014). The category termed “Other” was filled mostly by texts extracted for roles in Canada, the United Arab Emirates (UAE) and Hong Kong. Due to their lower representational percentage, these were merged into one category.

Dimension reduction

A Term-Document Matrix (TDM) presents the outcome of the text analysis on the information retrieved. This matrix represents a weighting scheme of the extracted terms against the documents included in the analysis. It is of course neither possible to represent all terms uncovered, nor useful (Karl et al. 2015). Consequently, only features with high explanatory value are extracted from the corpus of data, while associated “noise” is omitted (Miner et al. 2012). This process is termed as “dimension reduction” and involves summarizing the variables (terms in TDM) with low information content into several manageable variables. The resultant extracted variables are made from initial extracted features and contain the majority of information (Kotu and Deshpande 2015). Performing dimension reduction in text mining results in higher accuracy and prevention of overfitting problems, with minimal reduction of accuracy (Miner et al. 2012). The most common dimension reduction technique for text mining is Singular Value Decomposition (SVD). SVD converts a large corpus of features created through data mining into linear combinations, which reveal the underlying meaning, while maintaining the core of information across all documents (Miner et al. 2012). In view of the above, SVD was utilized as the primary method to deal with the problem of the large dimensionality in the present study (see Figure 1).

Association rule analysis

Association rule analysis is a branch of unsupervised machine learning that demonstrates hidden patterns in a dataset using recognizable rules (Kotu and Deshpande 2015). The technique matches frequent patterns and associations of variables in a dataset, predicting the occurrence of one item based on the occurrence of another item (Gollapudi 2016). Two algorithms, namely, *Apriori* and *Frequent Pattern Growth (FP-growth)* are commonly used to extract information from available datasets. Of these, *FP-growth* is seen as the most efficient for mining frequent patterns, and association rule mining (Kotu and Deshpande 2015). The efficiency of *FP-growth* lies in its ability to compress the data through transformation into a graph structure, called *FP-tree*. *FP-growth* also allows for creating maps of associations and is compatible with a wide range of programming languages and data analyses tools (Gollapudi 2016). Interested readers are referred to Gollapudi (2016) and Kotu and Deshpande (2015) for more details. Thus, *FP-growth* was selected as the algorithm for performing the analyses in the present study.

Tool selection

Text mining analyses can be implemented in RapidMiner, which is an open source data mining and business analytics software solution. RapidMiner provides an integrated environment for all the steps of the text mining process, alongside a graphical user interface for visualization of results (Klinkenberg 2014). Because association rule analysis can also be implemented in RapidMiner (Kotu and Deshpande 2015), RapidMiner Studio 7.5.001 was used in this study.

Findings of the study

From text to Term-Document Matrix (TDM)

The text mining procedure followed the accepted format, recommended by Miner et al. (2012), namely, first converting the text extracted from job advertisements into a TDM, then vectors were created using the operators, as illustrated in Figure 3. Interested readers are referred to Kotu and Deshpande (2015), for a detailed description of the process of converting textual data into a TDM.

Text mining algorithms treat words in a sentence as unrelated objects. These words are manipulated into *tokens* where the process of converting the text into bags of tokens is called *tokenizing*. Tokens form the TDM in which each token is an attribute and each document is a case. Filtering stopwords removed common terms (such as "a", "and" etc.), as illustrated in Figure 3. Stemming removes the suffixes of words, to form the word root.

A great many terms appear either too frequently or too infrequently across documents, making TDM very large, and sparse. Consequently, without removing them, text mining algorithms are adversely affected by the extra processing, increased variance, and lower accuracy (Ertek et al. 2014; Miner et al. 2012). To remove noise and create a TDM with meaningful tokens, a frequency-based feature selection approach is used. That is, terms with very few occurrences in very few documents are eliminated (Miner et al. 2012). It is recommended to prune the resulting term set using a 'prune method' in Rapidminer (Ertek et al. 2014), and hence terms that occur in fewer than 5 documents were pruned, following the steps described in the text mining study by Yalcinkaya and Singh (2015). By the same token, terms that were repeated in more than 190 documents were not taken into account in creating tokens. This is because, words that occur across the majority of documents are not informative (Miner et al. 2012).

As recommended by Kotu and Deshpande (2015), the *Porter stemming algorithm* was used. In common language, families of words and terms typically appear together. Findings and grouping such terms, called *n-grams*, provides new insights. Bigrams to 5-grams are common in text mining studies, however, the value for '*n*' can vary based on the nature of the corpus and size of documents (Kotu and Deshpande 2015). As illustrated in Figure 3, following the procedure described by Yalcinkaya and Singh (2015), bigrams, trigrams and 4-grams were tried, and 4-grams (e.g. assist_project_team_bim) were found to create the most meaningful tokens, and thus a 4-gram analysis was used. Three-word entities are not informative and have limited contribution to the corpus (Yalcinkaya and Singh 2015). With this in mind, and to make the number of entities manageable for analyzing purposes, a second filtering using minimum characters of 7 was added to the procedure. This was to remove any combination comprised of two three-word entities (removing 2-grams with 6 characters).

Major expressions were identified using the term frequency measures. These values were calculated for expressions extracted from the documents, to be included in the vector of terms. The process resulted in the creation of the TDM, with 199 rows and 545 columns for 'KSAs', and 199 rows and 631 columns for 'responsibilities', with 4-grams created (see Appendix 1 for details).

BIM manager across countries and position titles

Analyses of textual data requires conversion of textual information into numerical vectors in the form of structured spreadsheets, or a TDM matrix (Weiss 2005). The TDM matrix initially created was however both too sparse and too large. It had to be transformed into a matrix of smaller dimension in which the essential information sought could be distilled. The method used was the Singular Value Decomposition (SVD) technique. The SVD function was implemented to create singular vectors. As per Miner et al. (2012), 5 to 20 singular vectors are sufficient to extract key information from a TDM matrix. The singular vectors SVD Vector 1 to SVD Vector 20 were extracted. This resulted in a matrix with 199 rows and 20 columns, replacing the original TDM matrix. Thus, two such matrices were extracted, one for the TDM associated with 'KSAs,' and the other for the one related to 'job responsibilities' texts. The purpose was to ensure that the findings of the present study reflect a homogenous image of the BIM manager role, irrespective of the countries included in the dataset, or the different related position terms.

The distribution of dataset variables deviated from normal; variables such as *country* and *position* were categorical and binominal (for the latter, only 2 values). This necessitated using a nonparametric method. The *chi-square* test of independence is a statistical technique, which shows if two variables have any significant dependency, with literally no assumption about the distribution and the nature of data (Cronk 2016).

Having 'KSAs' and 'responsibilities' matrices of singular vectors and position and country as two variables, 4 different sets of hypotheses were to be tested, as discussed next. The test values and contingency tables for each test are included in Appendix 2.

KSAs across countries

$H_{0\text{-KSAs\_Countries}}$: *In the dataset, SVD values are independent from the country variable.*

$H_{a\text{-KSAs\_Countries}}$: *In the dataset, SVD values are depending on the country variable.*

As illustrated in Appendix 2, a *Chi-square* test of independence was calculated comparing the nature of 'KSAs' for the BIM manager role, as reflected in SVD values, across different countries. No significant dependency was found between the content of advertisements denoting 'KSAs' (SVD values) and different values for the country variable. That is, as illustrated in Appendix 2, the test values ($x^2(564) = 600, p = 0.142 > 0.05$) suggested that the null hypothesis ($H_{0\text{-KSAs\_Countries}}$) is to be retained.

KSAs for different terms

To test the dependency of KSAs on various terms (positions in the dataset), the hypotheses below were formulated.

$H_{0\text{-KSAs\_Positions}}$: *In the dataset, SVD values are independent from the position variable.*

$H_{a\text{-KSAs\_Positions}}$: *In the dataset, SVD values are depending on the position variable.*

The test was to assess if KSAs (reflected in SVD values) depend on the terms 'BIM Manager' and 'BIM Coordinator', despite the difference in term usage when referring to the position. The values of the test indicated no significant dependency between the content of advertisements denoting 'KSAs' (SVD values) and different countries values. That is, as illustrated in Appendix 2, the test values ($x^2(188) = 200, p = 0.261 > 0.05$) suggested that the null hypothesis ($H_{0\text{-KSAs\_Positions}}$) is to be retained.

Responsibilities across countries

$H_{0\text{-Responsibilities\_Countries}}$: *In the dataset, SVD values are independent from the country variable.*

$H_{a\text{-Responsibilites\_Countries}}$: *In the dataset, SVD values are depending on the country variable.*

A *Chi-square* test of independence was calculated comparing the nature of expected responsibilities for the BIM manager role (as reflected in SVD values) across different countries. No significant association was found between the content of advertisements denoting 'responsibilities' across different countries ($x^2(540) = 586.1, p = 0.083 > 0.05$), suggesting that the null hypothesis ($H_{0\text{-Responsibilities\_Countries}}$) is to be retained. As such, the nature of expected responsibilities for the BIM manager role turned out to be independent of the value of the country variable.

Responsibilities for different terms

To test the dependency of responsibilities on various terms (the two values in the dataset), the two hypotheses below were constructed.

$H_{0\text{-Responsibilities\_Positions}}$: *In the dataset, SVD values are independent from the position variable.*

$H_{a\text{- Responsibilities\_Positions}}$: *In the dataset, SVD values are depending on the position variable.*

The values of the test ($x^2(180) = 194.9, p = 0.212 > 0.05$) indicated no significant dependency between the content of advertisements denoting 'responsibilities' (reflected in SVD values) and different values for the position variable.

For the *Chi-square* tests above, the significance level was set at 0.05, and as such the confidence level was 95%. This shows that the findings demonstrate above 95% chance of the tested null hypotheses being true. With this in mind, there was no significant dependency revealed between KSAs as reflected in SVD values on various values of countries. Thus, the distributions and values of KSAs do not depend on the country values, neither are the KSAs affected by their corresponding country values. The same was observed for KSAs with regard to the terms used for referring to the position, responsibilities across country values, and responsibilities regarding terms for positions. Simply, KSAs and responsibilities are the same, regardless of the variations in terminology for referring to the position, and across the countries included in the dataset.

Association rule analysis of the BIM managers' 'responsibilities'

In order to reveal those main responsibilities expected of the BM role, the entire 199×631 TDM matrix was considered, as recommended by Miner et al. (2012). Once done, the underlying operational requirements of those responsibilities were extracted using association rule analysis. This analysis involves following the three sequential stages: *converting TDM to binominal values*→ *FP-growth algorithm*→ *identifying noteworthy rules*, as recommended by Gollapudi (2016).

That is, all variables in the TDM have to be in binominal format in order to feed them into *FP-Growth*. The nominal variables (term occurrences in TDM) were converted to binominals (*False* or *True* for occurrences of terms in documents). In using *FP-growth*, and the subsequent stage of identification of rules, several criteria were taken into account. Of these, two primary criteria are of particular importance in the interpretation of findings. Specifically, every association rule has to show a minimum *confidence* and a minimum value of *support*. *Support* for a rule is defined as Equation 1, demonstrated as a percentage, where $frq\ (x, y)$ shows the number of cases supporting a rule (x and y occur together), over the total number of cases in a dataset (*N*).

$$Support = \frac{frq\ (x,y)}{N} \qquad \text{Equation 1}$$

As for *confidence*, the value is defined as the frequency with which x and y occur together over the frequency with which x occurs in isolation, defined as Equation 2.

$$Confidence = \frac{frq\ (x,y)}{frq\ (x)} \qquad \text{Equation 2}$$

For the analyses, *FP-growth* was set to find a minimum number of 100 item sets and minimum value of *support* was set to 0.90 (default values for the function in RapidMiner). For identifying noteworthy associations, the minimum *confidence* was set to 0.75, to return reliable rules (0.75 was deemed adequate here, given 0.90 support value). These values are context-specific and user-defined, yet have to be identified in any association rule analysis to make the process replicable (Gollapudi 2016).

The outcome of the analysis is illustrated in Table 2. It is noteworthy of mentioning that RapidMiner provides a visualization of how different attributes are related to one another, alongside the *support* and *confidence* values for each rule. With the level of confidence selected, 72 rules were identified, and thus the graph was not legible. As such, the tabular values produced in Table 2 were used for items with confidence values above 0.90, resulting in identifying 15 rules. That was because, particular attention should be paid to high confidence rules (Kotu and Deshpande 2015). This practices is termed 'compact representation of frequent item sets', denoting that in association rule analysis, identifying a small representative set of high confidence items can derive the entire process (Tan et al. 2006). Interested readers are referred to Appendix 3 for a complete list of rules, and the developed procedures for rule mining in RapidMiner.

As illustrated in Table 2, the terms are presented in terms of stemmed items in relevant rules, generated from co-occurring item sets. The output (Table 2) demonstrates the items, and rules alongside their corresponding interest measures, to be used in filtering rules. Of these, *Confidence*, *Lift*, and *Conviction* are the most common criteria used for filtering rules by setting thresholds. Gain and Laplace also can be used in particular cases as interest measures for filtering rules (Kotu and Deshpande 2015). Interested readers are referred to RapidMiner (2014) for a detailed description of the measures produced as the output in conducting association rule analysis. As the interest measure recommended by Kotu and Deshpande (2015), *Confidence* was used in the present study.

Based on the stemmed items from Table 2, major responsibilities of BMs fall within five categories. These are *development*, *support*, *coordination*, *documentation*, and *software.* As an example for *development*, the rule {develop, project_team}→ {project} in Table 2, has a value of 100% for *confidence*. This indicates that in all cases that *development* co-occurs with *project_team, project* is present. For the rule {develop, document}→ {project}, such confidence is 93%. It is noteworthy of mentioning that in text mining analysis, entities like project_team are treated as individual entities, regardless of the meaning of the individual words that create them (Yalcinkaya and Singh 2015).

It can be inferred that as far as *development* activities are concerned, BIM managers have to focus on project team development, developing standards, documents, and processes (see Table 2). *Support* relates to coordination activities, processes, and software support. As illustrated in Table 2, *coordination* is another major responsibility for BIM managers, concerning standards, documents, and processes. Another major responsibility is about *documentation* where BIM managers are expected to document project teams' activities and processes, and in fact this responsibility, returning a confidence level of 0.94 for centrality of standards (see Table 2), proves to be an undoubtedly essential role. *Software* also plays a role in shaping the responsibilities of BIM managers. In essence, BIM managers are expected to oversee software and technology implementation on the project along with supporting project activities related to software (see Table 2).

Association rule analysis of the BIM managers' 'KSAs'

With the above equations and measures in mind, for the analyses of the entire 199×545 TDM matrix of "KSAs", *FP-growth* was set to find a minimum number of 100 item sets and minimum value of confidence was set to 0.95, the default value of the algorithm in RapidMiner. For identifying noteworthy associations, the minimum confidence was set initially set to 0.75, which resulted in no association rule. With the value set 0.65, 15 rules were identified, as illustrated in Table 3, and discussed below.

As illustrated in Table 3, experience or minimum years of experience plays a crucial role as an expected element of competency for the role. Minimum years of experience turned out to at the center of rules with the highest confidence values, denoting that minimum years of experience on construction project is a key element expected of BIM managers. This view was also reflected in having understanding of construction (reflected in the association of *construct* → *knowledg* in Table 3), with support= 0.36, confidence= 0.720 representing a noteworthy rule.

Software elements were however the primary hubs for the association rules, as highlighted on Table 3. Interestingly, AutoCAD and Navisworks were the most frequent software tools included among the association rules. This indicated the significance of competency in particular tools from specific vendors as a part of expected KSAs for the BIM manager role. These tools were also connected via several rules to the knowledge element showing the significance of an understanding of these tools, as expected by BIM managers in the market.

Discussion of the Findings

The UK, the USA and Australia are among the major markets currently utilizing BIM, with the USA making up around 30% of the total global BIM market (MarketsandMarkets 2017). Moreover, the UK, along with the USA, has the largest number of contractors implementing BIM (Bernstein et al. 2014). However, the similarity of 'responsibilities' and 'KSAs' of the BIM manager role across these countries, as revealed in this present study, contradicts the findings of Akintola et al. (2017), who claim that responsibilities and competencies associated with the BIM manager role are dissimilar. In fact, Akintola et al. (2017) refer to "peculiarities mainly in the broader scope of responsibilities" across different markets, due to "no uniform countrywide standards, specifications, and protocols guiding BIM implementation." Furthermore, the findings in the present study also bring forward new evidence challenging the widespread assumption promoted by Gu and London (2010), that BIM market requirements for BIM roles vary significantly across different countries. The present study overturns this assessment, providing extensive data-based evidence that 'responsibilities' and 'KSAs' associated with the BIM manager role can be considered identical across all major BIM markets, that is the UK, the USA and Australia.

The findings also shed new light on the relation between BMs and other roles in construction. Indeed, this study also settles the debate identified by Berlo and Papadonikolaki (2016) over whether there is a meaningful distinction between the role of BIM manager and BIM coordinator, finding that there is none. BIM managers and BIM coordinators do not represent two separate positions, but rather possess identical 'KSAs' and are required to undertake the same sets of duties. The role of the project manager is regarded as the most critical role existing on construction projects with respect to impacting project success (Ekrot et al. 2016), while also the closest role to that of the BIM manager in terms of ‘responsibilities’ and ‘KSAs’ (Rahman et al. 2016). In view of the identified ‘KSAs’ and ‘responsibilities’ extracted from the data, the legitimacy and sustainability of the BM role can be assessed by comparing it with the project manager’s role. In this regard, what stands out is: the most sought after requirement for both roles is ‘years of experience in delivering construction projects.’ Irrespective of the nominal title for the role used – whether project manager or BIM manager – project exposure is seen as the most important qualifying measure (Ekrot et al. 2016). Additionally, development of project teams, documentations and coordination activities are not specific to the BM role. According to PMI (2013), developing project teams is a direct responsibility of project managers. Coordination of teams, documentation of data, and attempting to promote knowledge sharing among active players on a project also falls within the domain of responsibilities carried by the project manager (Kasvi et al. 2003).

The only areas of discrepancy between the two roles are in regard to KSAs relating to use of certain tools and software, where it is the responsibility of BIM managers to support software utilization on projects. These however are not sustainable areas of discrepancy. Indeed, there is scope to acknowledge that BIM skills will increasingly become necessary for project managers and that they are not simply ‘add-on’ skills. The BIM market continues to evolve, with huge numbers of vendors continuing to enter and impact the market (Suwal and Singh 2017). In this process, project managers will gradually develop skills that facilitate increasing interaction with BIM software as BIM becomes a standard method of practice across the industry as a whole (Akintola et al. 2017; Lantelme et al. 2017). Once the BM role inevitably losses its monopoly position with regards to BIM knowledge, the role can be expected to drift across to other roles; and given the bulk of duties held by BIM managers are shared by the project manager, this is where the BIM manager role can be expected to ultimately disappear (Tyler 2006).

Practical Implications

The findings of this study offer a way forward for organizations already utilizing or planning to implement BIM. Rather than defining BIM manager as a standalone and separate role, they would be better to recognize that the role of the project manager will itself come to absorb the requisite skills now set aside under the role of BIM manager. In this regard, it would be more prudent to invest in strategies of continuous professional development of project managers in BIM software, standards and processes. The BIM manager role, as seen today, can be regarded as a transitory role with the temporary function of bridging the current short-fall in BIM expertise now being sought by construction companies (Akintola et al. 2017).

But in the fullness of time, with the rapid permeation of BIM across the construction industry continuing to flourish, the current deficit in BIM knowledge will recede and the current specialist role of the BM will no longer hold a unique monopoly on BIM knowledge, systems or processes. In view of such, resources would more prudently be allocated to training project managers directly, rather than perpetuating additional BIM specific roles within project hierarchies. The above outlines implications for policy-makers across the world who wish to mandate BIM use in projects, as they would have to acknowledge that BIM is more than an “add-on” in projects. Similarly, the study outlines an additional responsibility for industry leaders and senior managers to recognize the need and support the existing and nurture a new generation of project managers with BIM skills as a core component of their life-long learning. Additionally, at an individual level, the fact that BIM increasingly gains traction in construction, highlights that proactivity and resilience in one’s role is a key competence of future project managers in construction.

Conclusions

This study contributes to the body of knowledge of BIM-related knowledge, skills and roles. In particular, despite the extant number of studies on the role of BIM managers, this study is novel regarding its methodology and the findings put forward. First, the study provides evidence of the global similarity of the various markets in terms of the KSAs and responsibilities identified as requirements for the BIM manager role. Second, despite variations in terminology used in connection with BIM roles, the two most common being BIM manager and BIM coordinator, the associated KSAs and responsibility requirements do not in fact differ. The BIM manager and BIM coordinator roles, despite the nomenclature, are essentially the same. Third, the relatively unique methodology applied in the present study as well, as the availability of the data on the open-source domain, makes such analyses possible and reproducible, with the findings demonstrably reliable.

Finally and most significantly, the study settles the question on whether the BIM manager role can be expected to endure, or whether it is merely a transitional response to the dearth of expertise in BIM presently experienced, reflecting the construction industry's attempts to 'catch-up' with market demands for its utilization. Here, the BIM manager role is shown to be no different to that of the project manager, except in respect to BIM knowledge. As BIM knowledge permeates the industry, project managers can be expected to move up the BIM learning curve, and in so doing displace the only differentiating factor that presently exists between the role of BIM manager and project manager. This carries implications for the global construction engineering and management community, at both policy-making and industry levels, as BIM and the increasing digitalization of construction in general, provokes the sector to overtly embrace programs for life-long learning.

Certainly, however, this study too has its limitations. The main limitation being that while the claim is made that the findings are globally generalizable the job advertisements used, though from around the world (drawing upon North-American, European and Australasian contexts), were only culled from English language sources, for practical reasons. A wider sample, incorporating multiple language platforms may be considered in a future study. Moreover, the findings were based on a comparison between the BIM manager role and that of project managers. Comparisons with other roles in construction projects, such as of consultants or contractors, may also be worth considering.

Supplemental Data

Appendix 1, Appendix 2, and Appendix 3 are available online in the ASCE Library (www.ascelibrary.org).

Data Availability

Data generated or analyzed during the study are available at: https://figshare.com/s/06d762a91354833c50f4. Information about the *Journal*'s data sharing policy can be found here: http://ascelibrary.org/doi/10.1061/%28ASCE%29CO.1943-7862.0001263.

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