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Novel Approaches to Benchmark Capital Project Performance: An Application to Healthcare Projects

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Novel Approaches to Benchmark Capital Project Performance: An Application to Healthcare Projects

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Abstract

Novel approaches to benchmark capital project performance: an application to healthcare projects

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The University of Texas at Austin, 2020

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Benchmarking is defined as a process of continuous improvement based on the comparison of an organization's processes with those identified as best practice, thereby allowing for establishing improvement targets and promoting changes for better project outcomes. Despite its importance, incorporating it into an organization's routine is a cumbersome and time-consuming endeavor as it entails considerable time and human effort. Moreover, it lacks a systematic approach to capturing the similarity of projects for generating credible performance comparisons.

With the widespread implementation of Building Information Modeling (BIM) and technological advancements in the construction industry, new opportunities for improvement in benchmarking have emerged. In response, the overarching goal of this dissertation is to advance benchmarking practice by addressing major problems identified from current benchmarking processes in two different aspects. First, this research introduces a benchmarking framework that leverages BIM data for semi-automating a benchmarking data collection. To accomplish the goal, this research examines the

feasibility and functional requirements of such an approach by investigating diverse BIM models created for real-world projects. As a consistent approach to obtaining reliable benchmarking data from BIM is essential, this research also develops a formalized representation schema that transforms information stored in BIM into benchmarking data focusing on neutral information models. Second, this research proposes a new approach that finds groups of similar projects by capturing project similarity. In this research, critical and flexible features are selected with the use of data analytics and data mining techniques. Based on the features, the method generates a set of rules that produces different groups of similar projects by performance metric, which enables reliable performance comparisons. The studies presented in this dissertation are carried out by focusing on a healthcare benchmarking program.

This dissertation advances current benchmarking practices by streamlining the benchmarking process and allowing for more targeted metric comparisons. This dissertation contributes to integrating BIM with benchmarking practices by introducing a methodology to realize the BIM-based benchmarking and proposing a comprehensive and expandable representation schema to obtain reliable benchmarking data from BIM. It also contributes to establishing a systematic project grouping method that supports decision making for performance improvements.

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Chapter 1 Introduction

Project benchmarking is a systematic process of measuring and comparing a project's performance against that of other similar organizations in key business activities. It requires assessing project data through performance metrics and comparing the measures with similar data compiled by other organizations (CII 2014; Costa et al. 2006). The results, thus, enable an organization to establish improvement targets by explicitly identifying the gaps with their peers (Costa et al. 2006; Navon 2005). The general purpose of benchmarking - its function as an assessment process - is to encourage continuous learning for both managers and organizations. According to Garvin (1993), the greatest benefits of the benchmarking process are that it allows more efficient work and that it proactively involves managers in the process rather than depending exclusively on results. Benchmarking can be used to improve performance by helping managers understand the opportunities and practices required to achieve higher performance levels (Camp 1995). In a very competitive global environment, benchmarking is recognized as a common practice to manage capital projects (Suk et al. 2012; Yun et al. 2016), and various benefits contributing to the improvement of the Architecture, Engineering, and Construction (AEC) industry have been identified (Hwang and Zhao 2015).

Several benchmarking initiatives have been established for capital projects in different countries and industry sectors. However, current benchmarking approaches are susceptible to several limitations that can be improved upon so as to streamline the current benchmarking process and to enable organizations to gain better insights into their performance position. This chapter describes these limitations in the problem statement. To better explain the current benchmarking practice and explore the targeted problems, a representative benchmarking program tailored to healthcare facilities is described, focusing on its implementation process and associated challenges. This chapter also describes the research vision, questions, and scope, along with the organization of this dissertation.

1.1. PROBLEM STATEMENT

In the last two decades, several benchmarking initiatives have been established for capital projects in many countries such as the Construction Industry Institute (CII)'s Benchmarking & Metrics (BMM) and sector-specific benchmarking programs (e.g., healthcare and pharmaceutical projects) in the United States (U.S.) (Choi et al. 2016; Hwang et al. 2010), Construction Best Practice Programme (CBPP) in the United Kingdom (Hwang and Zhao 2015), as well as other initiatives developed in Brazil, Chile, Hong Kong, and Denmark (Du and Bormann 2014). As technology advances, most existing benchmarking systems have been ported to a web-based format which has advantages with regards to data collection, data quality checks, report generation while data security and confidentiality are well guaranteed compared to the traditional approach (i.e., paper-based survey instrument) (Costa et al. 2006; Lee et al. 2005).

In spite of the broad application of benchmarking practice, the AEC industry is still lagging behind in performance measurement and benchmarking practices compared to other industries (Navon 2005). The main reasons have been attributed to the high costs and rigorous efforts required to collect performance data (Hwang et al. 2013; Navon 2005). With the web-based benchmarking system, benchmarking users (or participants) can submit the data and get real-time benchmarking results; however, the time and effort required to enter project details into the online questionnaire are still one of the major concerns (Hwang and Zhao 2015). Moreover, considering the fact that data quality is the cornerstone of generating reliable benchmarks, it needs to be confirmed prior to calculating performance metrics and storing data into a performance database (CII 2014). Therefore, collected benchmarking data undergo a manual validation (or quality check) process for each project to ensure confidence in the source data whenever new project data is submitted (Stapenhurst 2009).

Another challenge of the current benchmarking process is related to the reigning paradigm of project uniqueness. Construction is a project-oriented industry, and each project is unique in terms of planning, design, construction, and site conditions. Credible benchmarking, thus, requires a method of identifying sets of similar projects for which the observed performance information can be "fairly" aggregated (Farris et al. 2006). However, the existing benchmarking practice lacks a robust and systematic methodology for capturing project similarity, instead of relying on ad-hoc techniques.

1.2. THE CASE OF HEALTHCARE FACILITIES

In order to better understand the current benchmarking process, along with limitations in current practice, this section investigates one of the representative benchmarking programs, namely the National Healthcare Facility Benchmarking Program (NHFBP). NHFBP was selected for this study because it has well-established performance metrics to measure healthcare-specific performance identified and prioritized by the domain experts (CII 2014; Kahn 2009). It was designed to measure a comprehensive list of metrics developed by the Construction Industry Institute (CII) in collaboration with a number of leading healthcare organizations from public and private sectors in the United States (CII 2014; Mulva and Dai 2009). Also, the NHFBP - in use since 2012 – hence, can be considered a mature program, and as of 2020, data from 89 distinctive healthcare projects have been entered into the NHFBP database. Therefore, NHFBP is chosen as an ideal benchmarking program to investigate the current benchmarking process. The following subsections provide detailed explanations on the NHFBP and specific challenges identified as barriers to implement the NHFBP.

1.2.1 National Healthcare Facility Benchmarking Program (NHFBP)

Benchmarking made its first appearance in the healthcare sector in 1990 with requirements of the Joint Commission on Accreditation of Healthcare Organizations in the U.S., which defined it as an assessment technique for monitoring the clinical, logistical, managerial functions (Braillon et al. 2008; Ettorchi-Tardy et al. 2012). Since then, several benchmarking frameworks have been established in the sector, such as the Performance Assessment Tool for Quality Improvement in Hospitals (PATH) designed by WHO (Groene et al. 2008) and the Health Care Quality Indicators (HCQI) (OECD 2001), and International Facility Management Association (IFMA) (IFMA 2013). However, the consistent goal of those benchmarking programs was to improve the quality of healthcare service delivery.

On the other hand, the costs associated with healthcare project delivery ranging from programming to commissioning phases may be a single large component of the capital costs, which reflects high capital investment, increasing technical sophistication, and a competitive marketplace. Although sector-specific benchmarking programs are commonplace in industrial and manufacturing settings, no prior effort was undertaken to create and administer a benchmarking program focusing on healthcare projects (CII 2013). Considering distinctive characteristics exhibited by the healthcare industry sector, CII began to develop various industry-specific benchmarking programs so that performance measures specific to different sectors are established, such as pharmaceutical / biotechnology (Hwang et al. 2010), and healthcare projects (CII 2014). The NHFBP is a sector-specific benchmarking program that was designed to enable healthcare owners and contractors/architects to compare their projects to similar ones completed by other organizations (CII 2014). During the development of the program, the research team identified and prioritized specific metrics to measure the outcomes of healthcare projects considering the key performance indicators (KPI). Those measures are principally concerned with the project attributes of cost, schedule, dimension, and planning using 254 metrics, which includes programming, design, procurement, construction, and commissioning phases of healthcare projects, as shown in Figure 1.

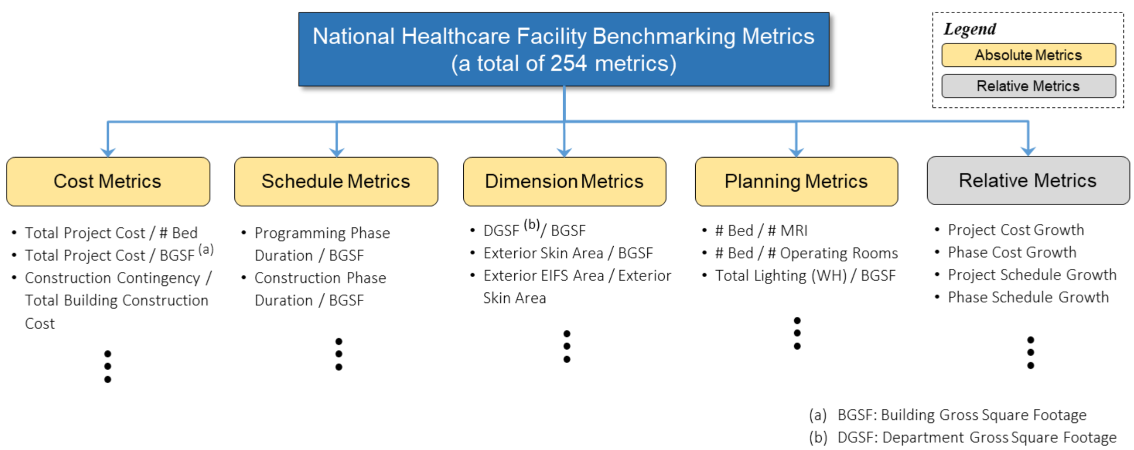


Figure 1: NHFBP metrics and categories

Overall, the cost metrics developed for the NHFBP highlight the actual or planned costs for the entire project or aspects of the project, relative to square footage or to other cost items, and the schedule metrics highlight the actual or planned project or project phase duration relative to Building Gross Square Footage (BGSF). The dimension metrics highlight, for example, the ratio of shelled space relative to BGSF, and the ratio of specific exterior envelope materials to the exterior surface area. The planning metrics, however, are designed to reveal issues related to the size of a facility and its department relative to beds or population to be served by the facility. Accordingly, the dimension and planning metrics can help rationalize the sizes or dimensions of spaces, the count of equipment relative to the entire facility, which are typically determined during the programming or early design phases. Those metrics can be used to identify specific ranges by which various project aspects could be validated. A full list of metrics is provided in Appendix 1.

1.2.2 Challenges of NHFBP Implementation

Overall, NHFBP is performed through six basic steps carried out by benchmarking users (i.e., participating organizations) and administrators (i.e., CII), independently or collaboratively (See Figure 2). First, a respondent collects necessary project data and completes an online NHFBP questionnaire for completed or in-progress projects. At the same time, CII provides training for designated representatives of each participating organization in order to ensure consistency in the project data entered in the system. This training covers the main aspects of CII's benchmarking programs such as metrics and program definitions, online data entry, and reporting, ensuring that participating organizations understand the meaning and intent of the questionnaire and its benefits (Mulva and Dai 2009).

Once the online NHFBP questionnaire is filled out and submitted, a validation process is carried out manually by CII staff to minimize or eliminate inconsistencies and errors. The goal of this step is to maintain data integrity so as to generate reliable benchmarks. During the validation step, CII reviews the submitted data and contacts respondents to resolve the problem whenever an issue is detected. Lastly, reporting benchmarking results are created using a project grouping algorithm based on four specific project characteristics, including healthcare project types, sub-type, project nature, and total project cost.

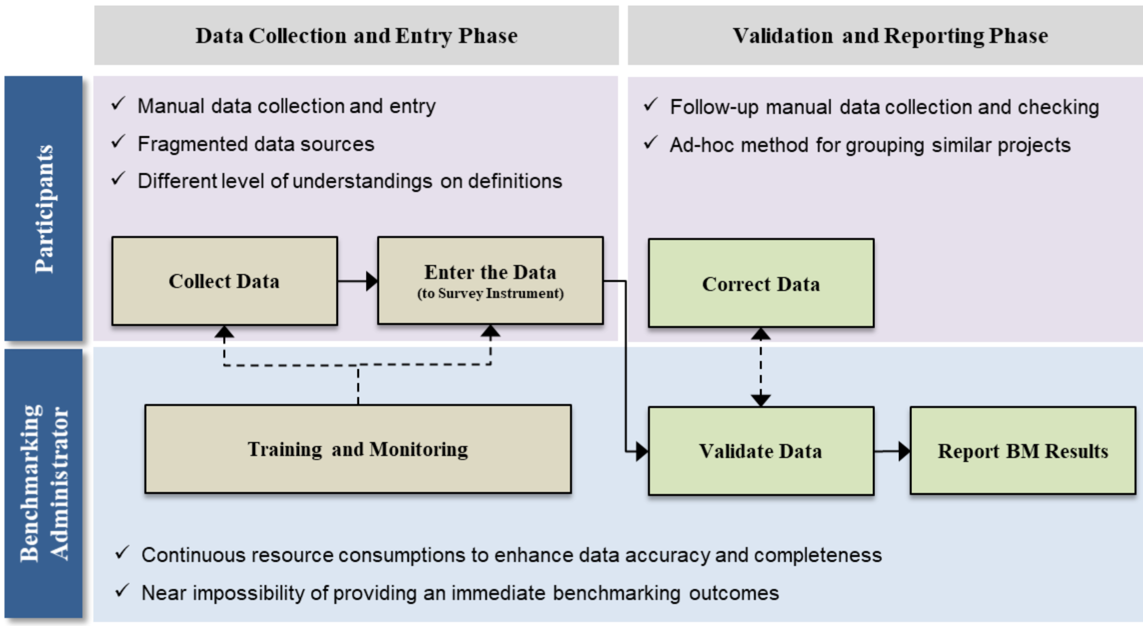
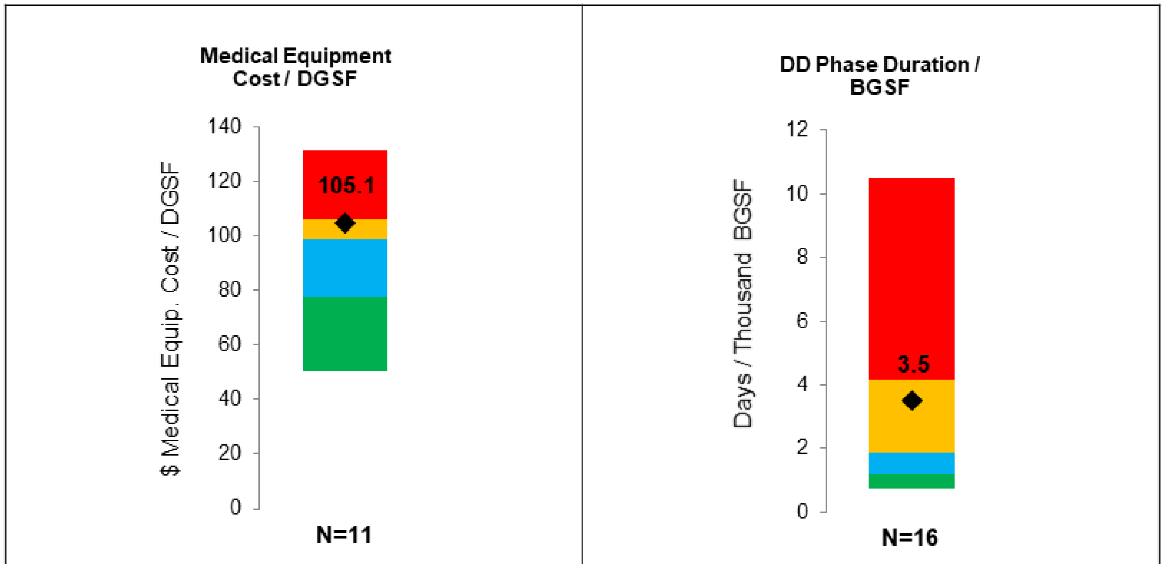


Figure 2: Schematic of the NHFBP process and main challenges

Figure 3 illustrates two examples of benchmarking results generated for two metrics, i.e., medical equipment cost (in USD) per departmental gross square footage (DGSF) and detail design phase duration (in days) per building gross square footage (BGSF). Each stacked rectangle represents 1st to 4th quartile ranges; each range includes the scores which fall between minimum to 1st quartile, 1st to 2nd quartiles (i.e., median), 2nd to 3rd quartiles, and 3rd quartile to the maximum of metric scores, respectively. The results also provide information about project characteristics used for selecting similar projects. For instance, a total of 11 projects were determined as similar projects for the medical equipment cost per DGSF, and those projects possess identical characteristics in terms of project type, subtype, and project nature, as shown in the figure. Given that ensuring data security is the hallmark of an effective benchmarking system, certain policies to protect the confidentiality of organizations submitting data are applied when creating benchmarking results. Based on the benchmarking results grouped in consideration of key project characteristics and the confidentiality rule, benchmarking results are generated and reported to the participating organization.



Min	1Q	2Q	3Q	Max	Min	1Q	2Q	3Q	Max
50.9	78.4	99.8	107.7	132.4	0.98	1.32	1.99	4.21	10.28

Comparison Criteria					
Metric	Project Type	Subtype	Project Nature	Cost Category	N
Medical Equipment Cost / DGSF	In-patient	Tertiary	Grassroots	All	11
DD Phase Duration / BGSF	Medical office	Business use	All	All	16

Note. DD, DGSF and BGSF stand for detail design, departmental gross square footage, and building gross square footage, respectively; and 1Q, 2Q, and 3Q denote first, second, and third quartiles, respectively.

Figure 3: Examples of benchmarking results

The main challenges identified from the current NHFBP processes are listed as follows:

(1) Manual data collection and entry

The NHFBP collects a vast amount of data that are used for measuring 254 metrics adopted to evaluate healthcare projects in various aspects. The main issue is that, by its nature of comprehensiveness, it requires a large amount of project information physically collected and submitted by participating organizations. Given that project organizations normally store and maintain those data in a fragmented manner with multiple formats, the time and efforts required to collect them are of major concern for participants. For instance, NHFBP collects project data concerned with a multitude of project attributes such as cost, schedule, dimension, and planning, along with a number of general project information.

Moreover, personnel responsible for completing and submitting the questionnaire may need to contact various stakeholders who have respective data while ensuring the completeness and accuracy of such data. A large number of data points, and the fragmented nature of current project data increases the burden on respondents and hinders the ease of data quality checking step. After finishing data collection, the data still need to be manually entered into the online questionnaire, which creates further opportunities for human-error (e.g., typing errors or mistakes). Although it all depends on project circumstances, collecting and entering benchmarking data to survey instruments, and validating the submitted data cannot be completed within a few days, considering the amount and diversity of data. In this regard, it is accepted that incorporating benchmarking into an organization’s routine is a cumbersome and time-consuming endeavor, provided that high costs and the efforts required to collect data (Hwang and Zhao 2015). Therefore, there is a need to provide users with a more streamlined data collection and entry.

(2) Manual data validation

After respondents complete the questionnaire, it is important to verify and validate the submission while resolving any omitted items, apparent consistencies or seemingly spurious values. The step to check the quality of submitted data is referred as data validation. The data validation is one crucial step for successful benchmarking because inaccurate or incomplete data may lead to drawing wrong conclusions on the decision makings for performance improvement (Stapenhurst 2009). Through the validation, data integrity can be maintained, which helps generate reliable benchmarks. However, the shortcoming of this step is that it is totally manual process implemented by CII staff and/or data providers.

At CII, major validation procedures are consisted of (1) checking whether data is complete and consistent, and (2) comparing data with submissions of other participants as well as to norms or expected values. The former is quite straightforward as missing (non-response) or inconsistent data should not be acceptable and should be queried by looking at the data and examining whether the value provided is reasonable. However, the latter is particularly a complex task in which the volume or complexity of data makes manual validation difficult or time-consuming. Another issue is that when these cases are found, CII needs to contact the data providers to ask for correction or justification, and this process needs to be repeated until all of the issues are resolved. Only after completion of the validation process, the data are added to the database.

(3) Lack of Systematic Approach to Capture Project Similarity

For credible benchmarking, the determination of a set of similar projects is essential in order for observed performance information to be compared on a like-for-like basis. However, the current approach to capturing the similarity of healthcare projects has certain limitations. First, for a small number of projects (a total of 89 healthcare projects), it is difficult to accommodate all four attributes (i.e., project type, sub-type, project nature, and total project cost) considering the number of categories for each attribute. In reality, the cost category is disregarded in most cases, and project nature is often ignored when a group of similar projects is determined for comparison. It is, thus, questionable if a set of grouped projects using one or two attributes is really similar enough for performance comparison across projects. Moreover, various metrics representing different aspects of performance are employed for NHFBP. Although the variability of the metric values may be influenced by different sets of attributes, a fixed set of four attributes is consistently used across all of 254 metrics. Provided that each metric is unique and might be associated with different project features, the fixed set of pre-selected features used in the current approach fails to capture differences in metrics' nature. The variation in each of NHFBP metrics may be accounted for different attributes that are more relevant to a corresponding metric, instead of the four fixed attributes. The level of similarities among grouped projects can be increased by using a flexible set of attributes that better explains the variation of target metrics.

The overall goal of this dissertation is to investigate novel approaches that the data collection and entry step can be semi-automated (or automated) and that project grouping can be systematically determined. In addition, it was envisioned that the new benchmarking approach proposed in this dissertation could obtain a wider range of project data with less human intervention and process them in an efficient manner, while providing benchmarking users with more insights into the benchmarking results than the current NHFBP does.

1.3. BACKGROUND RESEARCH

This section describes the key research area and topics as the points of departures, inspiring this dissertation as possible solutions to overcome the identified barriers to the NHFBP processes. With the widespread implementation of BIM in the construction industry along with advanced information technology, new opportunities for improvement in benchmarking have emerged. This research is based on the hypothesis that BIM can support a broad range of project data needed for the NHFBP, and data mining techniques can provide optimal solutions to group projects based on their similarities. As BIM can deliver relevant building information required for benchmarking, if it is used appropriately, a significant amount of time and effort in preparing benchmarking data can be shortened while reducing errors. Especially, Industry Foundation Classes (IFC) and Construction Operations Building Information Exchange (COBie), as neutral information models, can provide a consistent and robust approach for extracting necessary data without barriers of an interoperability issue. In addition, data mining techniques have been widely used to assist project stakeholders in complex decision making by allowing for the production of prediction models using historical data (Choi and Lee 2010). Given that benchmarking results arising from the ad-hoc determination of similar projects may lead to misinterpretation of relative project performance positions, data mining techniques can possibly be leveraged to systematically capture similarity of diverse projects and to generate reliable comparison groups for benchmarking. In this regard, the concept and application of BIM and data mining have been explored in the following subsections.

1.3.1 Building Information Modeling

BIM has been a growing development within the past years in the construction industry. BIM allows for representing and sharing information about a facility, forming a basis for collaborative decision making over the course of a project (Leite 2019).

BIM has rapidly changed the way that construction projects are delivered, by automating a broad range of manual processes. As construction projects are now becoming more complex and time and cost pressure have risen, more efficient and automatic practices for supporting decision making for project delivery have been proposed by a number of researchers (Chen and Luo 2014; Khaja et al. 2016; Lu et al. 2015; Wang and Leite 2015; Yang and Ergan 2015; Zhang et al. 2015). Examples of this research are BIM-based automated processes for cost estimation (Cheung et al. 2012), financial analysis (Lu et al. 2015), scheduling or planning (Liu et al. 2015), safety checking (Zhang et al. 2015), energy simulation (Aksamija 2012; Rahmani Asl et al. 2015; Welle et al. 2012), quality control (Chen and Luo 2014), and site layout planning (Astour and Franz 2014; Ji and Leite 2018, 2020; Kumar and Cheng 2015). Le et al. (2015) introduced a BIM-based methodology framework for automating cash flow analysis which has been done by integrating cost and schedule. Kumar and Cheng (2015) proposed an automated framework of creating dynamic site layout models by utilizing information from BIM. Also, Liu et al. (2015) presented a BIM-based scheduling approach that facilitates the automatic generation of optimized activity level construction schedules for building projects under resource constraints. Research conducted in this field reported BIM-based automated approaches reduce human effort and generate reliable or accurate outcomes, so BIM has the potential to automate current manual processes, which tends to be error-prone and time-consuming.

1.3.2 Information Extraction from Information Models

IFC standards and COBie specifications are considered mature and widespread in the Architectural, Engineering, and Construction (AEC) and Facility Management (FM) domains because they enable BIM models to be structured in a neutral format allowing for product data to be exchanged between designers, suppliers, constructors, and operators (Patacas et al. 2015).

IFC is an international open data standard for BIM in order to improve information exchange by maximizing the semantic possibilities for the representation of the model (Hartmann et al. 2017; Yang and Ergan 2015). As an object-oriented file format, building information is assembled as a set of objects, each object containing attributes describing the object in the IFC schema. In addition to objects, the IFC schema supports a predefined set of rules, functions, or types used to gain data associated with a certain domain such as architecture or structural engineering (Theiler and Smarsly 2018). The IFC model is highly diverse in the object types that can be represented, and in IFC 4, 766 object classes represent physical and conceptual objects in the different domains (Hartmann et al. 2017). As a subset of the IFC model, COBie is based on the facilities handover model view definition (Hartmann et al. 2017; Patacas et al. 2015). It comprises 16 concepts relating to managed asset information including space and equipment, but the key items to track for facility managers are (1) components that need operation/maintenance (O&M) and (2) spaces that need management (Yang and Ergan 2015).

Many studies investigated information representation for effective knowledge and information retrieval and reasoning in the realm of the AEC industry; for example, a IFC-based querying mechanism for vulnerability assessment during building emergencies (Leite and Akinci 2012), a formalized knowledge representation schema for spatial conflict coordination of mechanical, electrical and plumbing (MEP) (Wang and Leite 2016), a customized data representation for generating different views of project information using data stored in product models (Reinhardt et al. 2005), and a data representation schema to semi-automated tower crane planning (Ji and Leite 2015). Those studies reported the tangible benefit of using BIM as model-based information repositories as an alternative approach to streamline manual and repetitive processes.

1.3.3 Data Mining Techniques

The primary goal of data mining is to detect and predict qualitative and quantitative patterns in data, leading to new information and knowledge (Weng and Meng 2011). It has been used in diverse scientific domains, and many different methods and algorithms have been employed to perform predictive modeling in the construction management area. Some examples include predicting injury characteristics using large historical injury reports based on random forests and stochastic gradient tree boosting (Tixier et al. 2016), predicting heating and cooling loads of residential buildings based on random forests (Tsanas and Xifara 2012), predicting the occurrence and severity of accidents using occupational safety and health management system data based on neural networks (Goh and Chua 2013), classifying dispute propensity of public-private partnership projects using support vector machines (Chou and Lin 2013), and predicting appropriate retaining wall system using hundreds of excavation cases based on logistic regressions (Choi and Lee 2010). Table 1 presents descriptions of popular data mining techniques.

Compared to other data mining techniques, decision trees can analyze and classify project performance data in a human-interpretable format. The techniques such as neural networks, K-nearest neighbors, support vector machines, or random forests lack human-interpretability. While potentially providing superior prediction, these black-box techniques make it difficult for the modeler to validate and make sense of the final results

(Choi and Lee 2010; Zhou et al. 2016). On the other hand, decision trees have an advantage over other data mining techniques in that the method produces rules that are explicitly represented as a set of human-interpretable decision rules (Mistikoglu et al. 2015). Another advantage of decision tree is their flexibility in group extraction using a hierarchical tree-like structure (Mistikoglu et al. 2015), which is well suited for dynamic grouping of projects for performance comparisons.

Table 1: Representative data mining techniques and descriptions

Techniques	Descriptions
Decision trees (DT)	DT are well known for its ability to showcase learned knowledge. A decision tree contains a root node and a matrix of decision nodes which it terminates at the leaf nodes. Some drawbacks of a decision tree could be overfitting to the training data losing its ability to generalize and secondly, DT tends to favor the overrepresented classes leading to a biased outcome.
Random forests (RF)	RF is an ensemble model of the decision trees. RF perform classification based on the combined results of the decision trees using a bootstrap aggregating (bagging) method. As compared to decision tree, it is more robust in terms of generalizability.
Logistics regression (LR)	Branching from linear regression, LR is a linear model that perform classification instead of regression. It operates based on the natural logarithm, following a logistic S-curve, and has no assumptions such as normal distribution or equal variances across groups.
K-nearest neighbors (KNN)	KNN is a simple classifier due to its non-parametric properties and learning is performed based on its recall of all the similarity measures that are stored. One drawback is that this classifier required high computing power for large amounts of data.
Support vector machines (SVM)	SVM has been popular for its predictive ability among construction machine learning research as well as other industries. Using vectors algebra, it recursively computes the distance between all the points in the dataset and form a hyperplane between the closest points. This hyperplane forms the decision boundary which is inferred to perform classification

1.4. Research Vision And Research Questions

With recent technological advancements and the more widespread implementation of BIM in the Architectural, Engineering, Construction (AEC) industry, new benchmarking improvement opportunities have emerged. The overarching goal of this dissertation is to advance benchmarking practice by addressing major problems identified from current benchmarking processes in two different aspects. First, this research introduces a benchmarking framework that leverages BIM data for semi-automating a benchmarking data collection. To accomplish the goal, this research examines the feasibility and functional requirements of such an approach by investigating diverse BIM models created for real-world projects. As a consistent approach to obtaining reliable benchmarking data from BIM is essential, this research also develops a formalized representation schema that transforms data stored in BIM data into benchmarking data focusing on neutral information models. Second, this research proposes a new approach that finds groups of similar projects by capturing project similarity. In this research, critical and flexible features are selected with the use of data analytics and data mining techniques. Based on the features, the method generates a set of rules that produces different groups of similar projects by performance metric, which enables reliable performance comparisons. The studies presented in this dissertation are carried out by focusing on a healthcare benchmarking program.

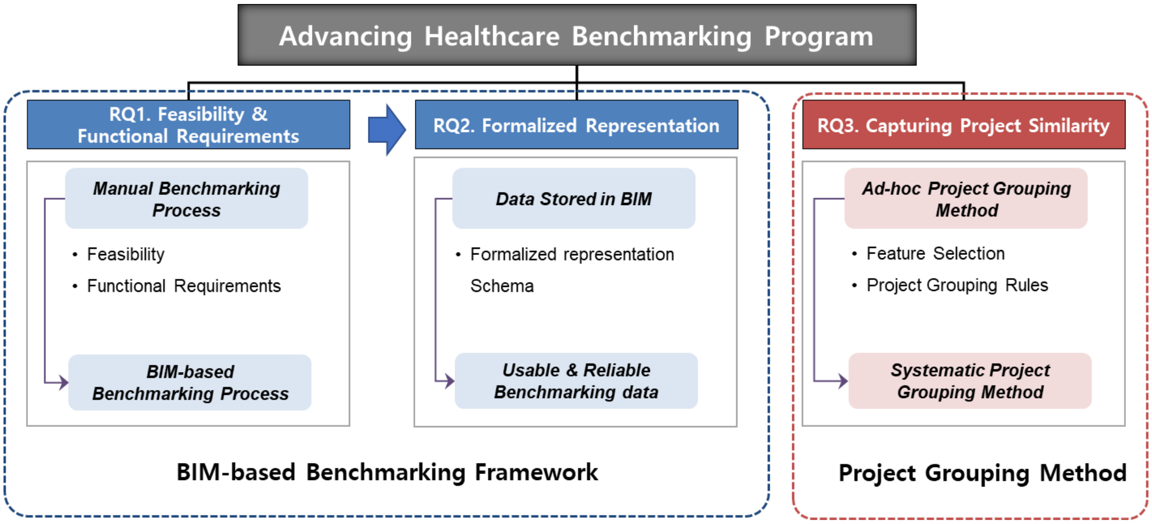


Figure 4: Research Vision

It is envisioned that this dissertation lays a groundwork of an automated benchmarking approach, leveraging emerging information technologies that allow large-scale project data to be captured and processed in an efficient manner and that provides benchmarking users with better insights into benchmarking outcomes. Figure 4 illustrates the research vision in three phases of three individual research questions. Note that the first research goal is addressed through the first two phases, and the second goal is addressed through the third phase in the figure. The following research questions have been developed to achieve this vision:

Research Question 1: What is the potential of BIM models to feasibly support data needed for NHFBP, and what are the essential functions of the BIM-based benchmarking tool to streamline the benchmarking process?

- What data are needed for measuring metrics adopted for NHFBP, and how well can BIM support the data?
- What essential steps are needed for implementing the existing NHFBP, and what functional requirements should be met to realize the BIM-based benchmarking tool?

This research question is a first step in the establishment of a BIM-based benchmarking for NHFBP by exploring the feasibility of the BIM-based approach, and the necessary functions in the envisioned approach. The results are presented as metric measurability with the use of BIM data as the benchmarking data repository and use cases, along with the mock-ups of a prototype system in Chapter 2.

Research Question 2: How can the data acquisition process from BIM models be formalized in order to obtain usable benchmarking data needed for NHFBP?

- How can NHFBP data be defined and classified into similar concepts?
- What objects and properties (or attributes) are associated with the NHFBP data?
- What processes are required to transform extracted BIM data into usable and reliable NHFBP data?

The goal of research question 2 is to develop a data representation schema to obtain usable benchmarking data for NHFBP by leveraging information stored in BIM. To fulfill the goal, this study investigates how BIM has been created and how its contents are structured to capture reliable data to be used for NHFBP, using real-world models of healthcare projects. The result of this question is presented in Chapter 3 as a formalized representation schema for obtaining reliable benchmarking data from BIM models, focusing on Industry Foundation Classes (IFC) and Construction Operations Building Information Exchange (COBie). IFC and COBie are structured in a neutral format allowing for product data to be exchanged among different stakeholders without the barrier of an interoperability issue.

Research Question 3: How can similarity of healthcare projects be captured for performance comparisons?

- What are the critical features that explain the variation of certain performance metrics?
- What methodology is well-suited for generating groups of projects for benchmarking purposes?
- How to generate a set of project groups using the data mining technique while satisfying a data confidentiality rule?

The goal of the third research question, presented in Chapter 4, is to develop a process for capturing similarity of healthcare projects. To achieve this goal, a comprehensive dataset collected from NHFBP data are analyzed to select a set of critical and flexible features that are closely associated with performance metrics using a data mining technique. The effectiveness of results derived from the proposed method is tested using statistical analysis and comparative analysis.

1.5. RESEARCH SCOPE

The overarching goal of this dissertation is to advance benchmarking practice by leveraging information stored in BIM models (addressed in research questions 1 and 2) and by developing a new project grouping method (addressed in research question 3), focusing on healthcare facility projects.

Research questions 1 and 2 are carried out by collecting real-world BIM models from on-going healthcare projects at the time of collecting the models now completed. The results of the research present the current status of how BIM models are produced in the healthcare sector and how the information stored in such models support the evaluations of NHFBP metrics. Both questions aimed to leverage BIM as a data source for CII's NHFBP. The representation schema proposed in research question 2 is based on available BIM data based on the findings from research question 1, excluding any data potentially unobtainable from BIM models such as cost and schedule information.

In this dissertation, "project grouping" refers to finding groups of similar projects for metric comparisons. All data collected from CII's NFHBP are analyzed to develop a new project grouping method, focusing on two representative cost and schedule metrics, i.e., total project cost (TPC) per building gross square footage (BGSF) and construction phase duration (CPD) per BGSF. Traditionally, the sets of pre-defined project attributes have been used for project grouping across all metrics, although there were slight discrepancies in project attributes used. Examples of these attributes include project types, project nature, project delivery method, and total project cost that are regarded as crucial to represent project characteristics. However, research question 3 does not assume the relative importance of project attributes in advance: instead, the entire project data are explored to determine key features that explain the variations of target metrics. To determine influential features, regression trees are used to predict the values of metrics, and the tree model is focused on the generation of the grouping rules, rather than the actual prediction of metric values.

1.6. READER'S GUIDE TO THE DISSERTATION

This dissertation is organized into five chapters. Chapter 1 presents the introduction, the case of healthcare facilities, research objectives and three research questions. Chapters 2, 3, 4 address research questions 1, 2, 3, respectively. Each of these chapters written as stand-alone documents that contain an introduction, literature review, research method, results, and discussions, and conclusion sections. Chapter 5 summarizes the dissertation's conclusions, findings, limitations and provides suggestions for future research.

Chapter 2 BIM-based benchmarking system for healthcare projects: feasibility study and functional requirements [1]

While project benchmarking based on key performance indicators is regarded as a crucial technique for mature project delivery in the construction industry, incorporating it into an organization's routine is a cumbersome and time-consuming endeavor as it entails considerable time and human efforts for collecting and providing project information, and validating the quality of collected data. To overcome this challenge, this chapter introduces an approach that leverages Building Information Modeling (BIM), which allows for a more streamlined benchmarking process. The approach presented in this chapter focuses on healthcare projects which have been benchmarked using a comprehensive set of cost, schedule, dimension, and planning metrics through a mature sector-specific benchmarking program at Construction Industry Institute (CII). As an initial step in the formulation of such a tool, this chapter investigates the potential of leveraging BIM for benchmarking through close scrutiny of contents embedded in real-world models collected from six healthcare projects. Functional requirements were, then, established to realize a BIM-based benchmarking tool for healthcare projects by developing conceptual process flow, use cases, and data flow diagrams. The requirements are further illustrated in mock-ups of a prototype system.

[1] Choi, J., Leite, F., and de Oliveira, D. P. (2018), previously published as "BIM-based benchmarking system for healthcare projects: Feasibility study and functional requirements." in the *Automation in Construction*, Elsevier, 96 (2018), 262–279. I, as the first and corresponding author, conducted all data analyses by collecting BIM models from healthcare projects, interpreted the results, and draft and revise the manuscript critically for important intellectual content.

2.1. INTRODUCTION

Benchmarking is a systematic, data-driven process of continuous improvements that involves gauging performance to identify, achieve, and sustain best practice (Camp 1995; CII 2012; Stapenhurst 2009). It requires assessing project data through performance measures (or metrics) and comparing the measures with similar data compiled by other organizations (CII 2014; Costa et al. 2006). The results, thus, enable an organization to establish improvement targets by explicitly identifying the gaps with their peers, and assist in promoting changes for better project outcomes (Costa et al. 2006; Navon 2005). Nowadays, in a very competitive global environment, benchmarking is recognized as a common practice to manage capital projects (El-Mashaleh et al. 2007), and various benefits contributing to the improvement of the Architecture, Engineering, and Construction (AEC) industry have been identified as a whole (Hwang and Zhao 2015).

In the last two decades, several benchmarking initiatives have been established for capital projects in many countries such as the Construction Industry Institute (CII)'s Benchmarking & Metrics (BMM) and sector-specific benchmarking programs (e.g., healthcare and pharmaceutical projects) in the United States (US) (Choi et al. 2016; Hwang et al. 2010), Construction Best Practice Programme (CBPP) in the United Kingdom (Hwang and Zhao 2015), as well as other initiatives developed in Brazil, Chile, Hong Kong, and Denmark (Du and Bormann 2014). Despite the differences behind performance measures and required data among difference benchmarking initiatives, the similarities in the findings reveal that they enable users to assess their competitive positions in the industry thereby assisting in performance improvements based on benchmarking outcomes (e.g., cost, schedule, planning, or productivity). Moreover, benchmarking programs focusing on operations and maintenance (O&M) phases are also established to enhance facility management performance. In particular, they have been largely implemented in healthcare organizations as an assessment technique for monitoring or improving operational, logistical, and managerial functions, which helps obtain better efficiencies in resource and operating management systems (Ettorchi-Tardy et al. 2012; International Facility Management Association (IFMA) 2010). As technology advances, most existing benchmarking systems have been ported to a web-based format which has advantages with regards to data collection, data quality checks, report generation while data security and confidentiality are well guaranteed compared to the traditional approach (i.e., paper-based survey instrument) (Costa et al. 2006; Lee et al. 2005).

Despite the broad application of benchmarking practice, the AEC industry is still lagging behind in performance measurement and benchmarking practices compared to other industries (Navon 2005). The main reasons have been attributed to the high costs and intensive efforts required to collect performance data (Hwang and Zhao 2015; Hwang et al. 2013; Navon 2005). Benchmarking based on project performance measures, by nature, requires a variety and vast amount of project data that is typically provided by project stakeholder through a survey instrument, so it is generally accepted that incorporating benchmarking into an organization's routine is a cumbersome and time-consuming endeavor (Costa et al. 2006; Hwang and Zhao 2015). Moreover, considering the fact that data quality is the cornerstone of generating reliable benchmarks, it needs to be confirmed prior to calculating performance metrics and storing data into a performance database (CII 2014). Therefore, in most cases, benchmarking data undergo a manual validation process for each project to ensure confidence in the source data whenever new project data is submitted (Stapenhurst 2009).

However, with recent technological advancements and the more widespread implementation of building information modeling (BIM) in the AEC industry, new benchmarking improvement opportunities have emerged. BIM represents a shared knowledge resource, or process for sharing facility data, forming a basis for collaborative decision making over the life of a project (Leite et al. 2011; Matthews et al. 2015). Research conducted in this field reveal that BIM-based automated approaches reduce the amount of human effort and generate reliable or accurate outcomes and BIM has the great potential for automating or semi-automating manual processes which tend to be error-prone and time-consuming (Aksamija 2012; Chen and Luo 2014; Cheung et al. 2012; Choe and Leite 2017; Gerrish et al. 2017; Ji and Leite 2015; Kumar and Cheng 2015; Lu et al. 2015; Oduyemi and Okoroh 2016; Reeves et al. 2015; Soust-Verdaguer et al. 2017; Zhang et al. 2015). As BIM can deliver relevant building information required for benchmarking, if it is used appropriately, a significant amount of time and effort in preparing benchmarking data can be shortened while reducing errors. For example, various CII benchmarking questionnaires are designed to collect project data for measuring as few as dozens and as many as hundreds of metrics which evaluate the projects in various aspects. While collecting a broad range of detailed project data allows assessing diverse aspects of project outcomes, it also increases the burden on respondents and hinders the ease of data validation. Although it all depends on project circumstances, collecting and entering benchmarking data to survey instruments, and validating the submitted data cannot be completed within a few days, considering the amount and diversity of data. Inspired by the aforementioned challenges associated with benchmarking implementation along with continuous developments of BIM technology, our ultimate goal is to develop a BIM-based benchmarking tool which is envisioned to leverage data stored in BIM models and provides users with a more streamlined data entry and analysis process. To accomplish our vision, a series of research studies are designed in order to tackle diverse and specific technical problems. As a preliminary study, this chapter conducts a feasibility study and identifies functional requirements of the BIM-based approach.

Among various types of building facilities, this research focuses on healthcare projects that have been benchmarked using a comprehensive list of metrics developed by the CII in collaboration with a number of leading healthcare organizations from public and private sectors in the US; the program is called National Healthcare Facility Benchmarking Program (NHFBP) (CII 2014; Mulva and Dai 2009). The NHFBP was selected for this study because it has well-established metrics to measure healthcare-specific performance identified and prioritized by the domain experts (CII 2014; Kahn 2009). Also, the NHFBP is recognized as a mature program that has been in use since 2012. As of 2018, data from 78 distinctive healthcare projects have been entered into the NHFBP database. In addition, the healthcare sector has taken the lead on BIM implementation and usage (Manning and Messner 2008; McGraw Hill Construction 2014; Merschbrock and Munkvold 2015).

BIM-based benchmarking for healthcare projects is an envisioned approach that leverages data obtained from BIM and provides participants with a more streamlined data entry and analysis process. It is believed that the development of technologies to facilitate this form of automated benchmarking represents a significant improvement in gauging project performance. BIM-based benchmarking can be achieved by developing a tool that is used to perform a range of functions required to benchmark project performance using data stored in BIM, including geometrical and non-geometrical attributes of elements (Gourlis and Kovacic 2016). As an initial step in the formulation of the tool, the goal of this study aims to investigate the potential of leveraging BIM as a benchmarking data source for the NHFBP and propose a range of functions required to realize a BIM-based benchmarking tool. This chapter, thus, describes how well BIM can support data needed for NHFBP by analyzing BIM contents using real-world models of six healthcare projects, and also presents essential functions of the envisioned tool. Functional requirements of the tool are further illustrated in mock-ups of a prototype system.

2.2. BACKGROUND

The NHFBP is a sector-specific benchmarking program which was designed to enable healthcare owners and contractors/architects to compare their projects to similar ones completed by other organizations (CII 2014). As a consortium of leading owners, engineering and construction contractors, and suppliers from both the public and private arenas, CII was established in 1983 to enhance the effectiveness of the construction industry (Choi et al. 2016). Since 1995, CII has developed statistically credible benchmarking programs that can be easily integrated into the project delivery process. Considering distinctive characteristics exhibited by industry sector, CII began to develop various industry-specific benchmarking programs so that performance measures specific to different sectors are established, such as pharmaceutical / biotechnology (Hwang et al. 2010) and healthcare projects (CII 2014). For the development of NHFBP, various performance metrics developed to measure construction project performance (e.g., cost, schedule, quality, safety, and productivity) (Hwang et al. 2010; Swarup et al. 2011; Yeung et al. 2009b; Yun et al. 2016) were studied to construct a base for establishing NHFBP metrics; however, most of the metrics did not consider specific characteristics that different industries exhibit. As effective performance measures are critical elements of successful benchmarking (Yeung et al. 2013; Yun et al. 2016), the measures adopted for the NHFBP were established through two-year research efforts by a team of 16 experts from academia and leading healthcare organizations (e.g., U.S. Department of Veterans Affairs, the U.S. Department of Defense, and Kaiser Permanente) through two-year research efforts (CII 2014). Those measures are principally concerned with the project attributes of cost, schedule, dimension, and planning using 254 metrics, which spans from programming, design, procurement, and construction through commissioning phases of healthcare projects. The program's participants made significant progress and as of July 2018, data from 85 completed healthcare projects have been collected through online NHFBP system and maintained in its database.

Overall, the cost metrics developed for the NHFBP highlight the actual or planned costs for the entire project or aspects of the project, relative to square footage or to other cost items, and the schedule metrics highlight the actual or planned project or project phase duration relative to Building Gross Square Footage (BGSF). On the other hand, the dimension metrics highlight, for example, the ratio of shelled space relative to BGSF, and the ratio of specific exterior envelope materials to the exterior surface area. The planning metrics, however, are designed to reveal issues related to the size of a facility and its department relative to beds or population to be served by the facility, in general. Accordingly, the dimension and planning metrics can help rationalize the sizes or dimensions of spaces, the count of equipment relative to the entire facility. Those metrics can be used to identify specific ranges by which various project aspects could be validated. The followings are the examples of NHFBP metrics to measure and evaluate cost or planning aspects: total project cost / BGSF; the number of beds / the number of Magnetic Resonance Imaging (MRI) machines; and BGSF / the number of Operating Rooms (OR). All the NHFBP metrics are provided in Appendix.

The NHFBP has been recognized as a meaningful tool for successful delivery of healthcare projects by providing quantitative comparisons of specific performance data (Badlato 2017; CII 2014). To that end, it collects a variety of data on performance. However, considering the amount and diversity of data to be gathered, the time and efforts have been of major concern for participants (Badlato 2017). For instance, these data are typically stored and in a fragmented manner with multiple formats and maintained by various stakeholders, since the data concern with a multitude of projects attributes (e.g., cost, schedule, dimension, and planning) along with a number of general project information (e.g., project location, project delivery method or nature). Moreover, after new data submissions are made by participants, CII staff should review the data with participants to ensure the validity prior to calculating metric values followed by generating benchmarks. The intensive manual input associated with the NHFBP implementation indicates that there is a need for a new benchmarking improvement which can provide a workflow that will make a benchmarking practice simpler and more efficient by decreasing human intervention.

In the meantime, BIM has been rapidly recognized to change the process of how construction projects are delivered by automating a broad range of manual processes. Examples include BIM-based automated processes for cost estimation (Cheung et al. 2012), financial analysis (Lu et al. 2015), scheduling (Liu et al. 2015), safety checking (Choe and Leite 2017; Zhang et al. 2015), quality control (Chen and Luo 2014), site layout planning (Ji and Leite 2015; Kumar and Cheng 2015), and sustainability (Oduyemi and Okoroh 2016; Soust-Verdaguer et al. 2017). In addition to these, researchers have introduced different tools or methods by investigating the use of BIM to support energy or performance assessment, thereby streamlining work processes associated with building energy efficiency simulation (Aksamija 2012; Gerrish et al. 2017; Reeves et al. 2015) or optimization (Welle et al. 2012).

In particular, the BIM maturity evaluation has been recognized as a domain where significant efforts have been made with respect to BIM-based performance assessment and benchmarking. Substantial work has done on the BIM Framework by Stanford's Center for Integrated Facility Engineering (CIFE), who proposed various indices and metrics that can be used to assess and benchmark the maturity of virtual design and BIM practices on specific projects using four survey forms concerning planning, adoption, technology, and performance (CIFE 2013). Another representative tool, Quickscan, was launched in the

Netherlands in 2011 by the Netherlands Organization for Applied Scientific Research (TNO) (Sebastian and van Berlo 2010; Wu et al. 2017) which is also designed to evaluate and benchmark BIM performance of organizations. While these tools provided great benefits for enhancing BIM maturity along with other existing tools [e.g., BIM Maturity Matrix (Succar et al. 2012); National BIM Capability Maturity Model (McCuen et al. 2011)], those use questionnaires to collect data which entails manual inputs from participants. Recently, a BIM performance benchmarking application was proposed to automatically collect BIM performance data from a variety of BIM users nationwide, based on a model of cloud computing (Du et al. 2014). The application utilizes the software as a service (SaaS) model of cloud computing to make the collection, aggregation, and presentation of benchmarking data autonomous and interactive. In their following research (Liu et al. 2015), the proposed initial list of metrics was developed and validated in order to figure out if those are suitable for the proposed BIM benchmarking application. However, the metrics and tool are focused on evaluating the achievement of BIM utilization focusing on BIM product or process (Wu et al. 2017) and thus it does not directly benefit their decision makings to improve project performance.

In summary, recent developments in the use of BIM promise to introduce major changes in diverse work processes in the AEC industry. BIM-based performance assessment and benchmarking have also been proposed to improve the previous manual process focusing on specific domains. However, there are no identifiable studies which utilize BIM for project performance benchmarking using a comprehensive list of performance metrics which can help users meter successfulness or rationality of healthcare project outcomes.

2.3. RESEARCH APPROACH

Motivated by the challenges associated with the NHFBP along with continuous developments of BIM technology, our ultimate goal is to develop a BIM-based benchmarking tool which is an envisioned approach to leverage data stored in BIM models and provides users with a more streamlined data entry and analysis process. This study is a preliminary step in the establishment of such a tool for healthcare projects using CII's NHFBP. As a first step to accomplish our vision, we need to understand the feasibility of the BIM-based approach, and what are the necessary functions in such a tool. Hence, the objectives of this chapter are two-fold; first, to investigate the potential of BIM as a data source for CII's NHFBP, and second, to establish functional requirements of the envisioned tool. In this context, a two-step roadmap was undertaken to accomplish said objectives as shown in Figure 5.

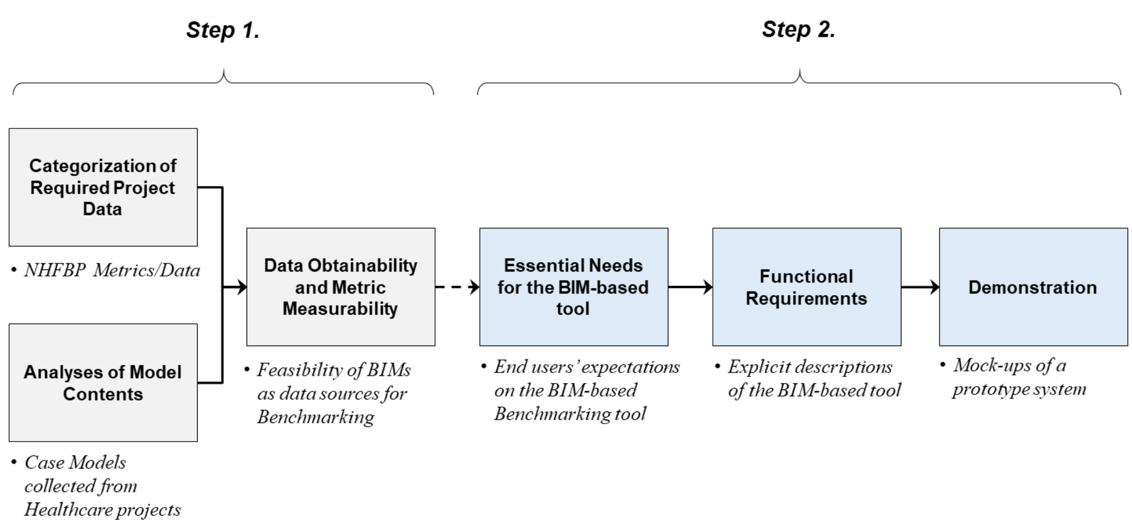


Figure 5: Research approach

The first step aims to identify what NHFBP metrics can be directly or semi-directly measured from BIM data. To begin with, the NHFBP metrics were investigated to categorize the necessary benchmarking data into similar concepts such as room or space, mechanical equipment, and cost. This classification is intended to facilitate identification of whether specific concepts exist in models, based on the categorized components and their attributes (Afsari and Eastman 2014). At the same time, the authors collected a variety of models from completed or on-going healthcare projects, including three in-patient hospital projects and three medical office building projects. When solicited, native modeling files (e.g., Autodesk Revit, and Graphisoft ArchiCAD) or Industry Foundation Classes (IFC) models were prioritized so as to investigate models in which data remain in the format they were created with full graphics and data integrity. Model contents were then analyzed to identify what benchmarking-related information can be supported by BIM, and what metrics are potentially measurable when BIM is used for the NHFBP. This analysis was carried out by comparing elements and their attributes produced in models with categorized concepts using the NHFBP metrics. All the collected models were produced in Autodesk Revit, and various tools (e.g., Autodesk Dynamo, Assemble System, and Solibri Model Checker) were used when model contents were investigated.

The second step was designed to document functional requirements which are descriptions of the envisioned BIM-based benchmarking tool. The goal of this step was to understand what is required for the tool in terms of functionality, to accurately communicate this understanding with software developers, and to ensure that a system meets design specifications later on (Wiegers 2003). To establish the requirements, knowledge elicitation was completed through several rounds of focus group and brainstorming sessions involving experts along with interviews with current NHFBP users. The participants of all focus groups consisted of 9 experts in BIM, benchmarking, and healthcare domains, and the distribution of year of experience ranged 5 to 20 years. All authors participated in these sessions to prioritize and determine functional requirements of the tool during a 3-month period. Functional requirements were represented using (1) a set of use cases that describe software requirements, and (2) and data flow diagrams (DFD) that model the functions of the envisioned BIM-based benchmarking approach. A demonstration was conducted using publicly available healthcare facility models (NIBS 2017) with minor modifications to support sufficient data for measuring certain metrics. One of the authors presented this vision to the group of industry experts and researchers at various CII activities and events held in 2016. Accordingly, the comments received from the groups are reflected to improve the vision.

2.4. FEASIBILITY OF USING BIM IN NHFBP

This section examines what data are obtainable and investigates what metrics are potentially measurable when data stored in BIM are used for NHFBP. As a first step, the definitions of NHFBP metrics were studied, and individual data points used to measure them were then classified into similar concepts. The classified data are illustrated in Figure 6 with respect to eight categories along with the number of data which belong to each category. The NHFBP adopted 254 metrics to evaluate healthcare projects using 173 individual data. It should be noted that the number of metrics is greater than that of required data since the same data are used for different metrics; for example, BGSF is frequently used for measuring several distinct metrics such as actual project cost per BGSF, BGSF per building footprint area, and duration of Schematic Design (SD) per BGSF. Likewise, Departmental Gross Square Footage (DGSF) is needed to evaluate numerous metrics, e.g., DGSF per BGSF and shell size per DGSF.

The objective of the data classification is to determine the existence of specific concepts in models in terms of the categorized components and their attributes. When 173 data are grouped by concept, it was found that there are some data that cannot be classified into certain categories such as team size, population (i.e., the number of people which the hospital was designed to serve in specific geographical areas), and the number of fatality cases. Those data are categorized as “others” which comprises 36 respective data. As shown in Figure 6, the majority of required data for NHFBP metrics is related to cost and space, while duration (time period of specific phases) and bed-related data are not required as often in comparison to other categories. For clarification, most data under the building envelope category represent the square footage of each exterior finish system, and those under both bed and medical equipment categories mean the counts of each item used in the hospital (CII 2014).

To explore data stored in the models, three in-patient hospital projects and three medical office building projects (MOB) were collected, and data stored in those models were explored. The in-patient hospital is defined as a facility capable of providing definitive inpatient care, where staffed and equipped to provide diagnostic and therapeutic services (CII 2014); on the other hand, a MOB is a freestanding ambulatory care facility that is physically separated but administratively attached to a medical center commonly referred to as a “parent facility” (CII 2014). While the models donated by a limited number of projects were used for this analysis, the six models of the projects consist of a total of 46 individual component models that were created by a variety of trades or disciplines and were compiled by integrating them into six federated models.

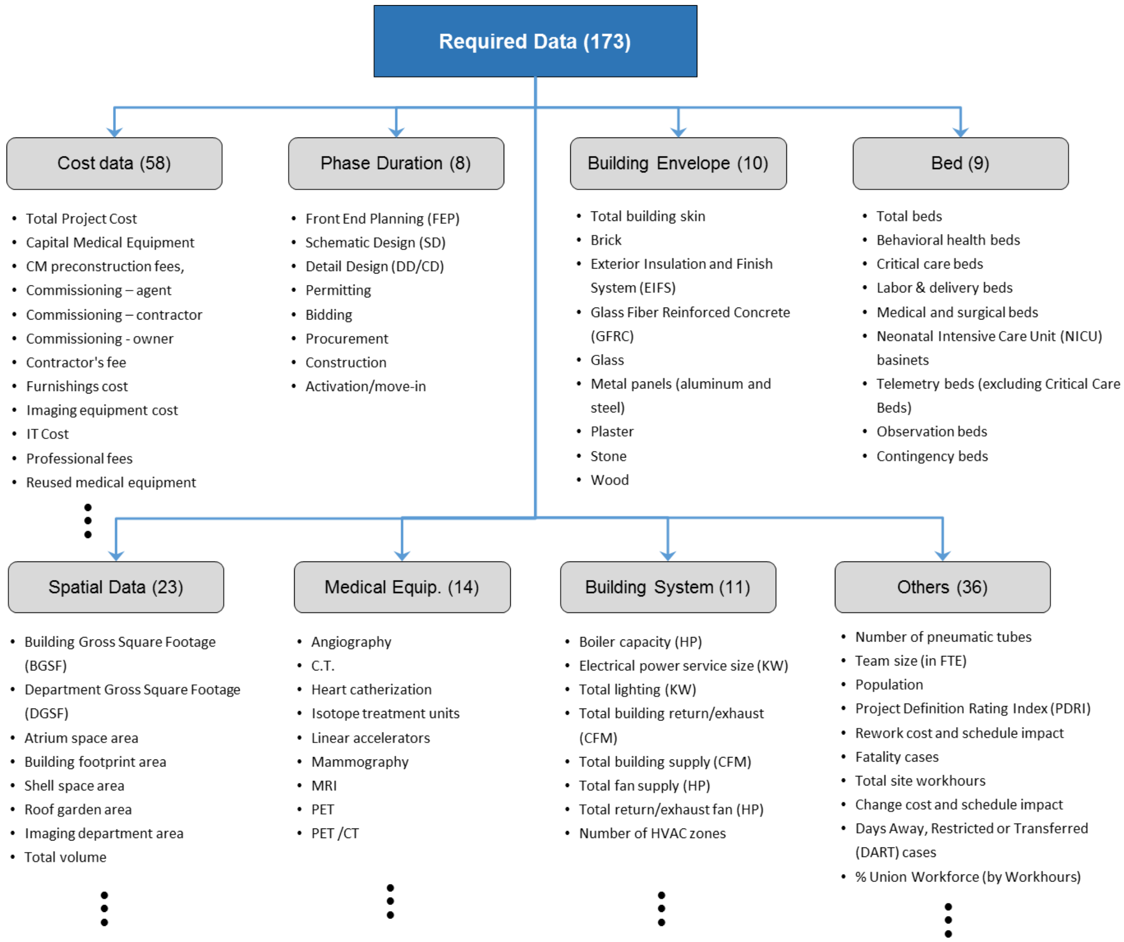


Figure 6: Required data for NHFBP metrics by category

BIM can be created in separate, distinct component models and these separate models may originate from a variety of project stakeholders, including owner, architect, structural engineer, contractor, sub-contractors, and suppliers (Beach et al. 2017; Solihin et al. 2016). It is worth noting that Integrated Project Delivery (IPD) has materialized as a delivery method that can most effectively facilitate the BIM usage for healthcare projects (Porwal and Hewage 2013). The coupling of BIM and IPD enabled a level of collaboration as IPD facilitates an opportunity to work in a single BIM environment with the goals of improving efficiency and reducing errors, even though each party produces its own model. As presented in Table 2, different types of component models were collected by project; while projects A and C produced a variety of discipline-specific models combined as a federated model, relatively a limited set of component models were produced from projects B and E.

Table 2: Collected model types (disciplines) by project

Discipline	In-Patient Hospital			Medical Office Building (MOB)		
	Project A	Project B	Project C	Project D	Project E	Project F
Architectural	✓	✓	✓	✓	✓	✓
Structural	✓	✓	✓	✓	✓	✓
Medical Equipment	✓	✓	✓			
Mechanical	✓		✓	✓		✓
Electrical	✓		✓	✓		✓
Piping or plumbing	✓		✓	✓		✓
Site	✓		✓			
Furniture	✓	✓	✓	✓		
Power & Data	✓	✓				
Telecommunication	✓					

Note: All the models are in RVT format and produced at design phase.

In addition to the variance in the type of component models, it was found that each project contains diverse elements in the same component model; for instance, while the architectural model in Project A contains some of plumbing fixtures and mechanical equipment elements, Project B does not include these elements. This variability in component models was observed for most of the collected models, which implies that a common industry-wide BIM standard is not established, regarding what types of models should be produced with what elements for each project (Cerovsek 2011; Jones 2017; U.S.

Department of Veterans Affairs 2010), and those decisions on modeling protocol are most likely company-specific or even project-specific. Moreover, BIM can be produced to accomplish diverse goals (e.g., multi-trade coordination, visualization of the design intent, or 4D or 5D simulations) (McGraw Hill Construction 2014; U.S. Department of Veterans Affairs 2010), which can also affect how BIM should be designed and thus impede standardization of BIM production (Kreider and Messner 2013).

Table 3: Required data for NHFBP by category and their availability by case model

Category	Unit	Case models					
		A	B	C	D	E	F
Cost / schedule							
Cost	US Dollars	×	×	×	×	×	×
Phase duration	Days	×	×	×	×	×	×
Building envelope							
Total building envelops	Square Feet	●	●	●	●	●	●
Specific material	Square Feet	●	●	●	●	×	●
Bed							
Total beds	Each	●	●	●	×	×	×
Specific bed	Each	●	●	●	×	×	×
Space / Room							
Area	Square Feet & Cubic Feet	●	●	●	●	●	●
Room	Each & Square Feet	●	●	●	●	●	●
Medical equipment	Each	●	●	●	×	×	×
Building system							
HVAC Zone	Each	●	×	●	●	×	×
HVAC system	Varies	○	×	○	○	×	○
Electrical system	Varies	○	×	○	○	×	○
Others	Varies	○	×	×	×	×	×

Note: ● denotes fully available; ○ denotes partially available; × denotes not available.

Model elements and their properties can be extracted by federating component models into a single composite model, which references data from linked models (Beach et al. 2017). The federated model enables access to elements and their parameter information in linked models (Beach et al. 2017; Solihin et al. 2016). Using federated models of three in-patient hospitals and three medical office buildings, data extraction was conducted to investigate how information needed for NHFBP metric calculations was embedded and retrieved from BIM. Table 3 presents the existence of data in the case models by NHFBP data category, which consists of cost/schedule, space/room, medical equipment, and material quantity information.

As shown in Table 3, data under cost or schedule categories were not possible to obtain from six models as relevant properties were not added to model elements. BIM offers a capability to generate quantity take-off (QTO) which serves as a basis for cost and schedule estimation, reliable cost estimation and scheduling cannot be attained without applicable external databases (e.g., unit cost or productivity database) to supplement QTO data (Hartmann et al. 2012; Kim et al. 2013a; Lee et al. 2014). On the other hand, space or room, and their properties were embedded in all the collected models, which includes room or space names, their areas and volumes, department assignment, perimeter, floor, etc. BGSF and room elements were also created and designed using proper boundary lines in all the models across all six models. For building envelope, the models reflected the appropriate geometric properties of the materials as material name and dimensional information were defined through customized families and types. The elements representing bed and medical equipment (e.g., MRI, ultrasound) were produced in the models of in-patient hospitals, which are projects A, B, and C; however, the models for MOBs did not contain beds in their models. This result makes sense considering the fact that MOBs are more focused on outpatient care rather than in-patient care which needs regular hospital beds (CII 2014). On the other hand, the building system category includes various data concerning HVAC, plumbing, and electrical system in terms of system capacity or the number of equipment (or device) or zone. While the elements representing the system were inserted in some models, limited properties were embedded to the elements; for example, boiler or cooling capacities, electrical power service size were not defined in the corresponding elements in most cases.

Based on the information embedded into the case models, Figure 7 presents the percentage distribution of the metric measurability when BIM data are used. Before the measurability is examined, data obtainability from BIM was examined so as to determine which ones among 176 data needed for the NHFBP can potentially be supported by BIM. Due to the variance in data inserted in the case models, it was assumed that a data is obtainable from BIM when any of the six models stored and maintained the data. This is a reasonable assumption considering the goal of this study which is to investigate the potential of BIM for benchmarking using real-world models, and maximum possible data were, thus, used for this analysis.

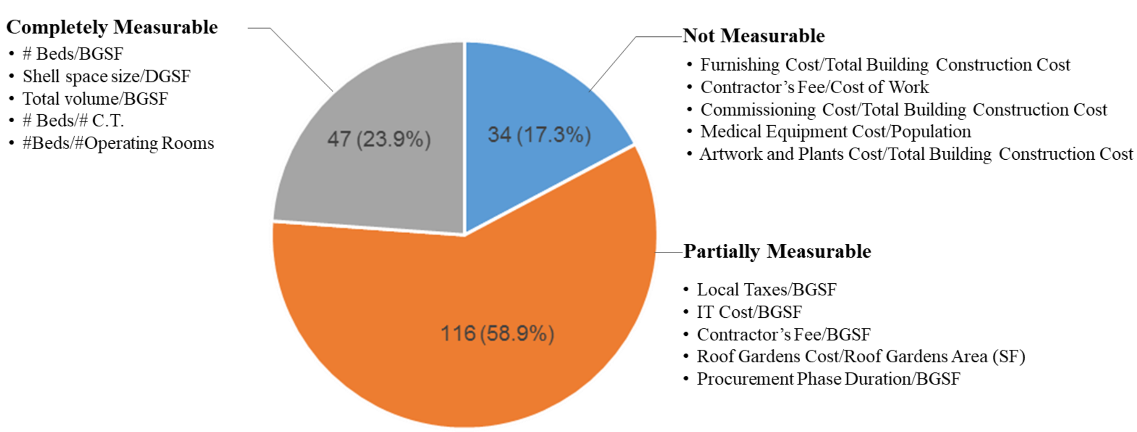


Figure 7: Measurable CII Healthcare benchmarking metrics using BIM data

In Figure 7, completely measurable metrics indicate ones that can be fully evaluated using BIM data; e.g., BIM can provide all the required data for measuring a metric of BGSF per the number of beds. On the other hand, partially measurable metrics mean that BIM does not contain one of the data needed to measure the metric values so additional data input is required. An example of partially measurable metrics is actual project cost/ number of beds. In this metric, the number of beds can be obtained from models, while external data sources are required to obtain actual project cost. Lastly, there are metrics that cannot be measured using data stored in BIM, which accounts for 23.9% out of 254 metrics. Furnishing cost per total building construction cost, contractor's fee per cost of work are examples of the not measurable metrics.

The result of analysis of the metric measurability shows that 82.8% of the metrics (200 metrics out of 254 metrics) are partially or completely measurable when BIM data is used for NHFBP. This outcome implies that BIM, although supplemental data are required for measuring all the metrics, can provide a considerable amount of data required for measuring NHFBP metrics and thus it has potential to reduce efforts and time needed for data collection and entry. It will also help to minimize human intervention. This BIM-based benchmarking approach is also promising, given that the use of BIM, coupled with diverse simulation or management tools, is expected to steadily grow (Love et al. 2015; Matthews et al. 2015).

2.5. Functional Requirements

This section outlines functional requirements to provide computational support for the BIM-based benchmarking tool, and further illustrate how the envisioned tool can be implemented for NHFBP. As discussed in the previous section, BIM, potentially, can support a large amount of data needed for metrics adopted in the NHFBP as the portion of partially or completely measurable metrics are considerable. To identify the functional requirements in relation to the BIM-based benchmarking tool, knowledge was elicited through focus group and brainstorming sessions among the research team comprising of individuals having expertise in BIM, benchmarking, and healthcare project domains based on the findings from the previous section. The major goal of the discussions was to establish the vision of BIM-based benchmarking tool, as well as the components of functional requirements for the tool, to streamline the NHFBP process to reduce manual efforts while guaranteeing a model confidentiality or intellectual properties, and data security.

At first, the essential needs from end-users (e.g., CII, and expected benchmarking participants and tool developer) who are concerned with the implementation of the ultimate product, were defined and documented as narratives along with their priorities based on high, medium, and low criteria. Eliciting essential needs from end-users and prioritizing them are critical components (Wiegers 2003). Table 4 describes highly expected functions commonly agreed by end-users. Based on the essential needs, a conceptual process flow diagram was developed to array sequences that are important for the tool to perform by functional units, as displayed in Figure 8. It is important to note that models will not be submitted to CII for implementation of this initiative; instead, they will reside at user's devices, and only necessary data for NHFBP will be transferred to CII database due to confidentiality and intellectual property issues associated with BIM products (Porwal and Hewage 2013). We envision that the tool can be an add-in application for existing BIM platforms, which can be used to perform a range of functions required to benchmark the project performance using BIM data. The Revit database can be queried in *Visual Studio* through *C#* and the application can be set up in the user's end (Autodesk 2018).

Table 4: Prioritized essential needs for the tool

ID	Items	Description
SN-1	Access security	The tool shall allow only authorized users to enter the tool.
SN-2	Model confidentiality	The tool shall extract only necessary data from models and the models shall not be uploaded or shared through the tool.
SN-3	Data storage	The tool shall transfer extracted data from models to a remote server (i.e., CII NHFBP database).
SN-4	General project information collection	The tool shall enable users to provide general project information (e.g., project location, nature, and project delivery method) which is hardly stored in models.
SN-5	Data extraction & transformation	The tool shall extract data stored in models based on the metric tables (i.e., mapping a list of metrics to required variables along with their unique identifiers) transform them into a single number representing the values of variables so that the metrics can be calculated.
SN-6	Determination of available data	The tool shall detect metric availability based on data stored in BIM and allow users to review the availability.
SN-7	Missing data management	The tool shall enable users to provide any missing data which is not contained in models.
SN-8	Metric selection	The tool shall allow users to select the metrics at their discretion. The tool shall enable users to navigate a list of available metrics by metric category (i.e., cost, schedule, dimension, and planning).
SN-9	Linkage with CII database	The tool shall receive metric values of those that user has selected, from the CII NHFBP server where metric calculation occurs.
SN-10	Removal of abnormal data	The tool shall identify statistical outliers among the metric values received from the NHFBP server and excludes the cases before reporting.
SN-11	Report generation	The tool shall enable users to receive benchmarking outcomes through key reports.

Based on the conceptual process flow diagram, functional requirements were elicited for explicit descriptions of the tool. There are several types of requirement models such as Data Flow Diagram (DFD), entity-relationship diagram (ERD), state-transition diagrams (STD) or use case diagrams (Wiegers 2003). Functional requirements in this section were developed using use case diagram and DFD. Two requirements models are discussed in the following subsections.

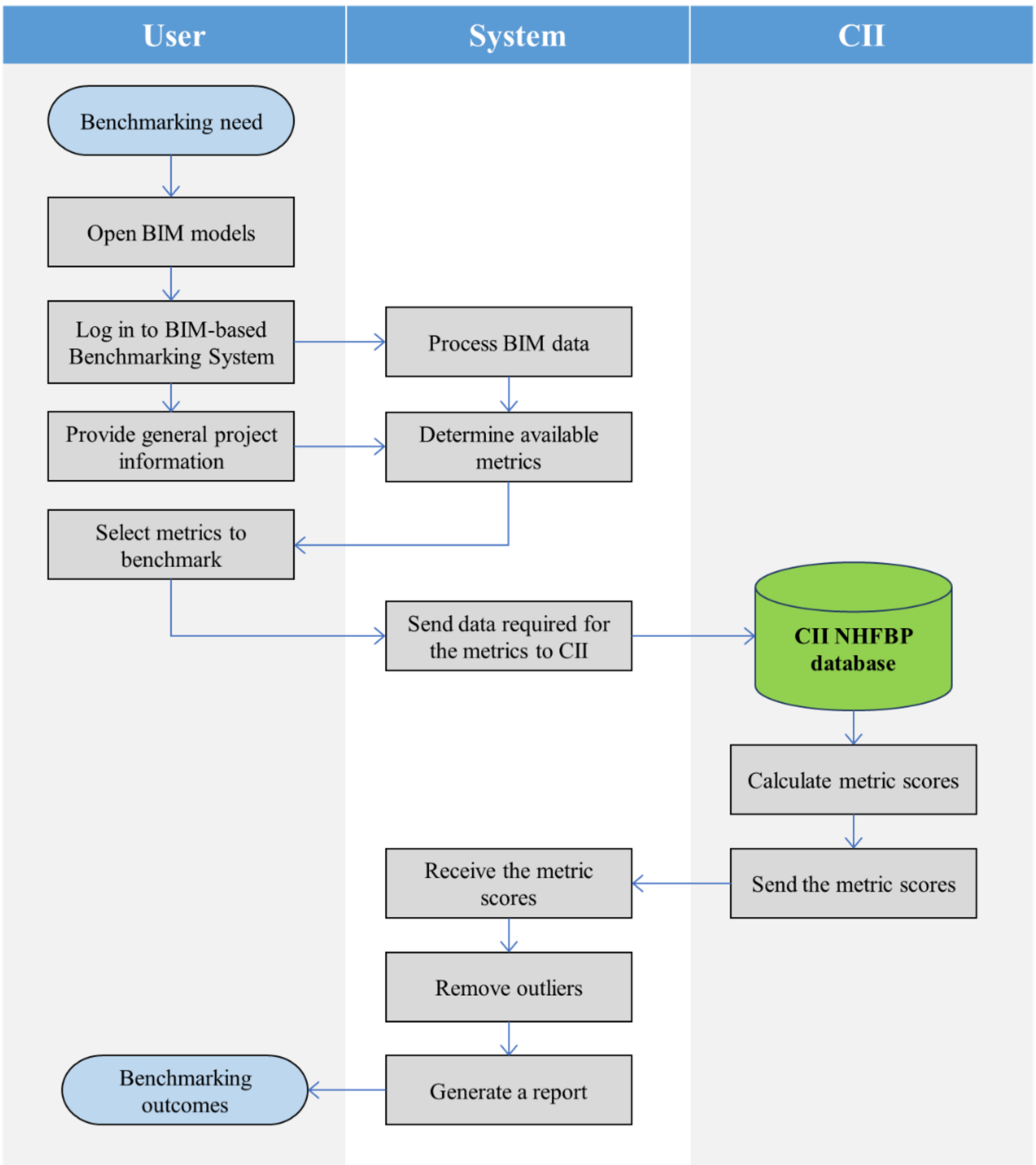


Figure 8: Conceptual process flow diagram for BIM-based benchmarking for NHFBP

2.5.1 Use Cases

This section details major services (functionality) provided by a BIM-based benchmarking tool. A use case describes a sequence of interaction between a system and an external actor (Booch et al. 1999). Use cases shift the perspective of requirement development to discussing what users need to accomplish so the objective of the use case is to describe all tasks that users will need to perform with the system (Wiegers 2003). In the diagram, an actor is a person, another software system, or a device that interacts with the system to fulfill a target goal and a use case typically represents a major piece of functionality that is complete from beginning to end and captures a contract between the stakeholders of a system about its behavior (Cockburn 2001).

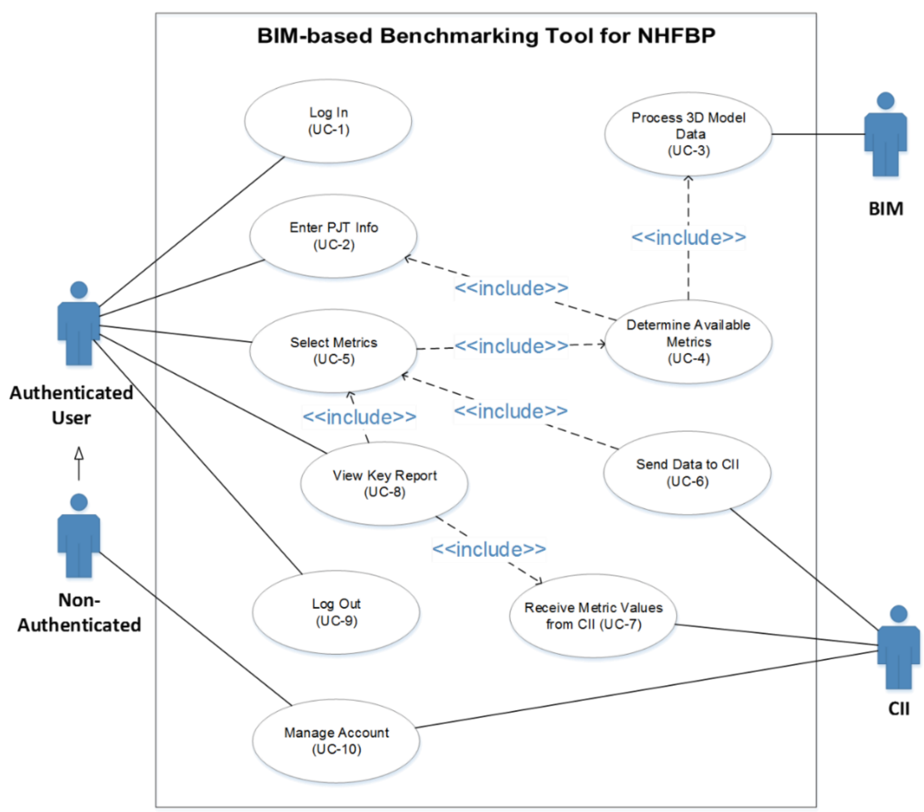


Figure 9: Use case diagram of the BIM-based benchmarking tool

As shown in Figure 9, the BIM-based benchmarking tool can be accessed by registered members when they log on to the system, whereby each user can enter general project information (UC-2), and then ‘Select Metrics’ (UC-5) to benchmark at user’s discretion. As BIM does not contain all the necessary data as identified from the previous section, UC-2 is implemented to collect both project information and other necessary data to measure specific metrics (e.g., cost, schedule). ‘Determine Available Metrics’ use case includes ‘Process Model Data’ (UC-3) and ‘Enter PJT Info’ use cases (UC-2) because data generated from two use cases allow the users to recognize which metrics are available for benchmarking in UC-5. ‘Send Data to CII’ use case which interacts with both 3D Models and CII, includes UC-5 because data to be sent to CII are determined depending on users’ metric selection implemented in UC-5. This use case is critical as it makes users to choose data to be submitted to CII and to preclude any sensitive data being shared with CII. ‘Receive metric values from CII’ use case is included in ‘View Report’ because a report generation requires metric values to be obtained from CII. The metric values can be calculated using data that were sent to CII, obtained from UC-6. Also, ‘View Report’ use case is extended by ‘Print Report’ use case, which enables the user to print out the report, optionally. Finally, CII can access the system to manage any users requiring user accounts by activating or deactivating user accounts. Note that descriptions of the required functionality of individual use case (i.e., use case descriptions) are listed in Appendix 2.

The Data Flow Diagram (DFD) is a structured analysis and design method, which identifies the transformational processes of a system, the collections of data that they system manipulates, and the flows of data between processes, stores, and the outside world (Wiegers 2003). While a use case diagram shows a specification of a service or function, it does not provide all the functions needed in interface management and/or scenario definition and analysis (Rumbaugh 1991; Wiegers 2003). As the connections between entities and processes in DFDs have a direction, and data flows along these connections, DFDs and use-case modeling concepts are complementary and can be used together to aid in conceptualizing a system design (Rumbaugh 1991).

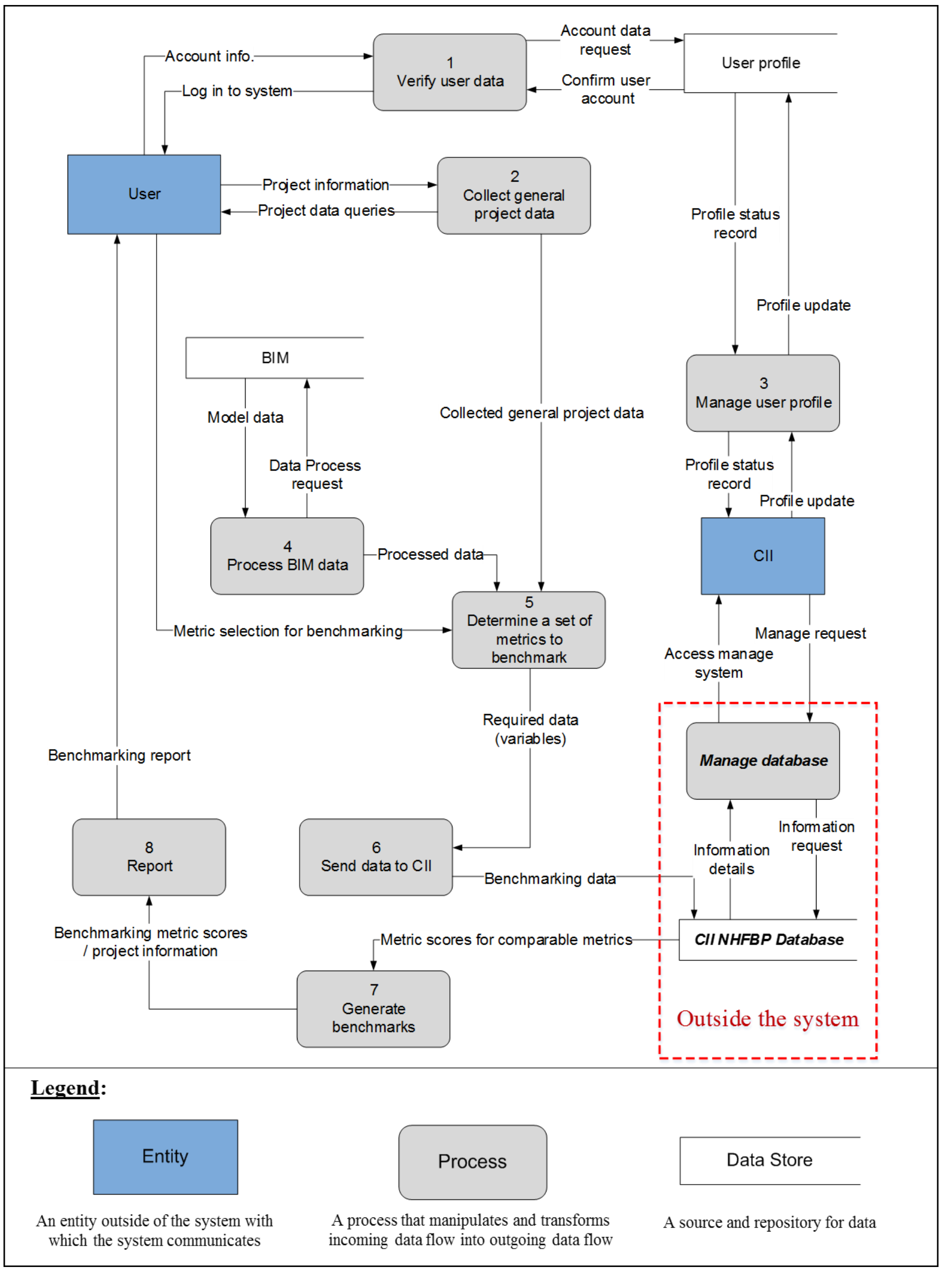


Figure 10: Level 0 data flow diagram for the model-based benchmarking system

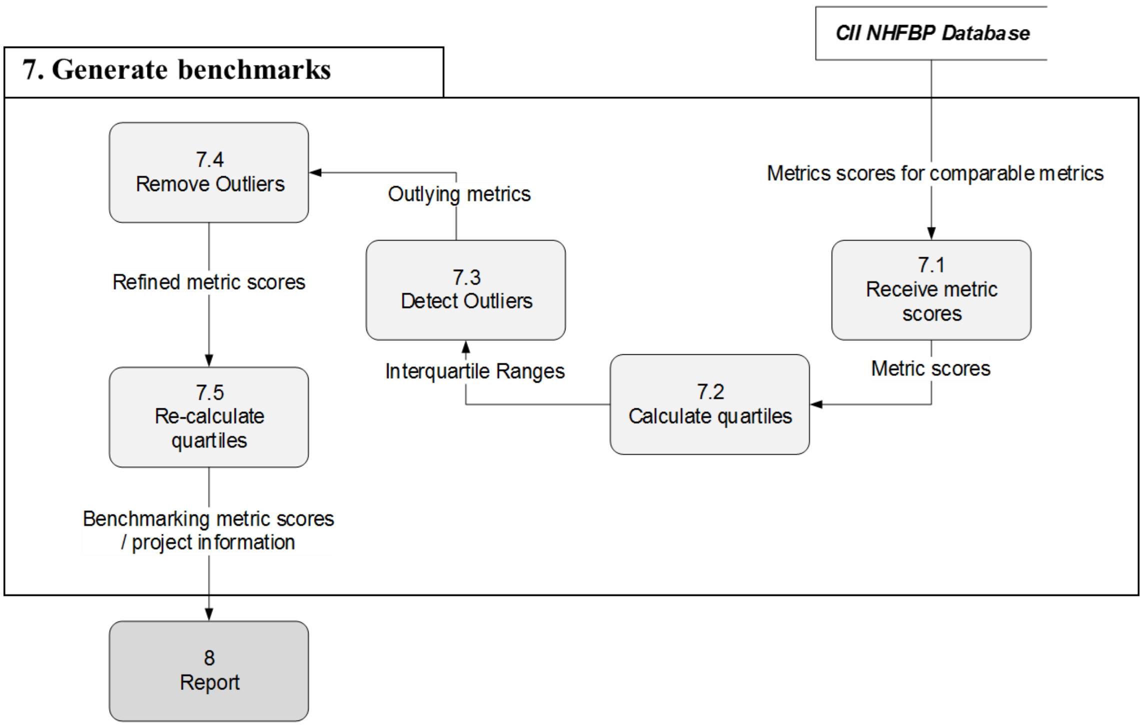


Figure 11: Level 1 data flow diagram for the BIM-based benchmarking tool

The DFD, as illustrated in Figure 10, shows the level 0 DFD for the BIM-based benchmarking system which contains eight processes, two external entities, and two data stores excluding ones executed outside the system. A benchmarking user can log in to the tool by 'Verify user data' process, and the details are provided by 'User profile' data store which is managed by CII. A user can initiate the 'Collect general project data' process, which will result in having general project data sent to 'Determine a set of metrics to benchmark' process along with processed data resulting from 'Process BIM data' process which receives BIM data from 'BIM' data store. A user selects metrics to benchmark through 'Determine a set of metrics to benchmark' process, which takes processed data and collected general project data from processes 2 and 4. 'Send data to CII' process is initiated once required data is received from ‘Determine a set of metrics to benchmark’ process, and CII receives benchmarking data through ‘Send data to CII’ process. CII can also initiate ‘Manage database’ process to manage CII NHFBP database which sends the metric scores of comparable metrics to ‘Generate benchmarks’ process. Then, a user can receive a benchmarking report through ‘Report’ process, which takes benchmarking metric scores and project information as input from ‘Generate benchmarks’ process.

The DFD can be decomposed into component sub-systems and identify the transaction data in the data model (Wiegers 2003). The distributions of metric scores can be easily skewed by outliers so the ‘Generate benchmarks’ process is critical for generating reliable benchmarking outcomes by addressing outlying metric scores from a set of metrics scores and increasing confidence in the final result. Figure 11 shows a level 2 (i.e., Child) DFD for the process of the level 1 DFD, which delineates how the system is designed to address outliers so as to increase confidence in the final benchmarking results. Prior to generating benchmarks, all metric outcomes need to be screened to remove statistical outliers in order to delete values so extreme that their inclusion would be likely to distort the statistical summaries of metric scores produced. The same technique used to identify statistical outliers in most statistical texts was employed, which is based on the concept of boxplot and involves the use of interquartile range (IQR) (Schwertman et al. 2004). The IQR, as a measure of statistical dispersion, is computed based on 1st and 3rd quartiles of the distributions of metric scores. Then, ‘Detect outliers’ process finds and eliminates outlying scores which are any values lying more than 3 times the IQR below the 1st (i.e., 25th percentile) or above the 3rd quartile (i.e., 75th percentile) (Schwertman et al. 2004), and sends remaining scores to ‘Re-calculate quartiles’ process which re-generates quartiles and other descriptive statistics without outliers. Finally, ‘Report’ process receives the metrics scores and project information from ‘Re-calculate quartiles’ process which takes refined metric scores as input from ‘Remove outliers.’ Through ‘Generate benchmarks’ process, all metric scores are checked to verify that they are within appropriate ranges and inappropriate data points are removed whenever identified. The refined scores are, then, used to generate benchmarking results in the report, which will help users to diagnose their projects, and identify specific performance that they need to improve.

2.5.2 Implementation example

This section illustrates the proposed functional requirements in a mock-up of the BIM-based benchmarking tool. To demonstrate the tool, a set of benchmarking metrics was selected from a complete list of NHFBP metrics. Focusing on a small set of metrics can be more effective in demonstrating the feasibility of a prototype system (Gediga et al. 2002; Wiegers 2003), and verify that the concept has the potential of being implemented according to its purpose rather than investigating all the metrics. Out of the 254 metrics used in NHFBP, 20 metrics that are perceived as relatively important by the NHFBP users, were equivalently chosen from all the different categories of metrics for the demonstration purpose. Figure 12 presents the metrics under each metric categories selected for the tool demonstration.

The tool can be installed as an add-in to Revit (Autodesk 2018). After the installation from a user side, a link is created under benchmarking tab of Revit as shown in Figure 13. Once a user is logged into the tool (see Figure 14), the user can provide general project information through open-end text box and checkbox questions (e.g., project name, type, and forecasted total project cost and schedule) on the general project information tab (see Figure 15). At the same time, the tool extracts data stored in the model according to the list of data required for evaluating NHFBP metrics on the back end. After finishing entering data on the general project information, the user can select metrics to benchmark based on their availabilities in BIM, which is determined by the tool behind the scene. The metric availability can be determined using separate metric tables (e.g., metric IDs, data IDs, and their relationships) which represent a linkage between a specific metric and required data to measure it through their unique identifiers. After the user finishes selecting metrics, the system sends data to CII and fuses such data with existing NHFBP data and receives metric scores from CII automatically. Then, a window for summary presentation of the benchmarking results will pop out and shows the benchmarking outcomes as quartile charts by metric (see Figure 16). As aforementioned, in a report, quartile cut-offs are used to define categories of performance after removal of outliers. The tool also allows users to print out the report and to save it in their machines.

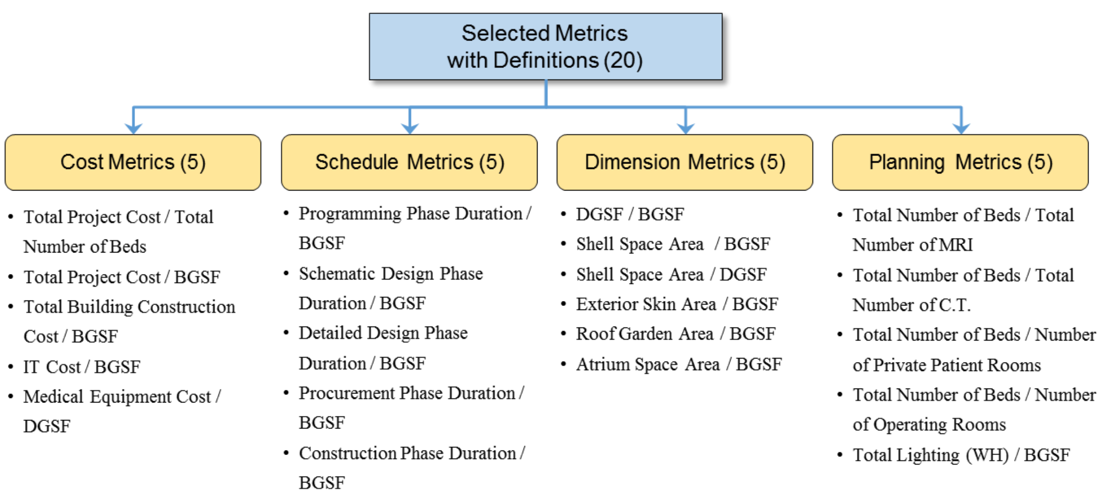


Figure 12: Selected metrics with definitions

To demonstrate how the BIM-based benchmarking report can be interpreted for performance analysis, an excerpt of benchmarking outcomes is presented in Figure 17. Each stacked rectangle represents 1st to 4th quartile ranges; each range includes the scores which fall between minimum to 1st quartile, 1st to 2nd quartiles (i.e., median), 2nd to 3rd quartiles, and 3rd quartile to the maximum of metric scores, respectively. For cost and schedule metrics, the quartile chart allows users to intuitively perceive their relative positions (shown as large black diamonds) based on color schemes to quickly represent each quartile range for metric scores, given that low scores are considered better than high ones. However, dimension and planning metrics do not allow an interpretation for what values are better or worse because those are targeted to identify specific ranges by which dimensional or planning aspects could be validated; therefore, no color schemes are used for quartile ranges in these metrics.

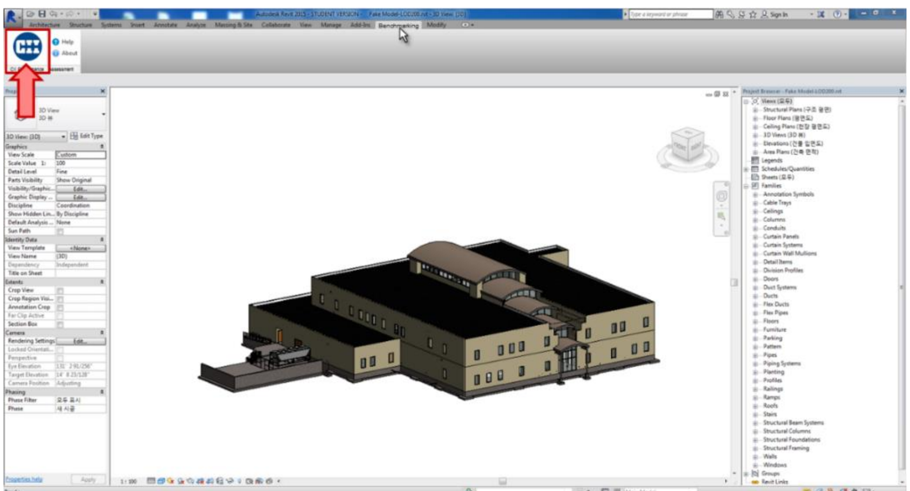


Figure 13: Add-in (Revit) for the BIM-based benchmarking system

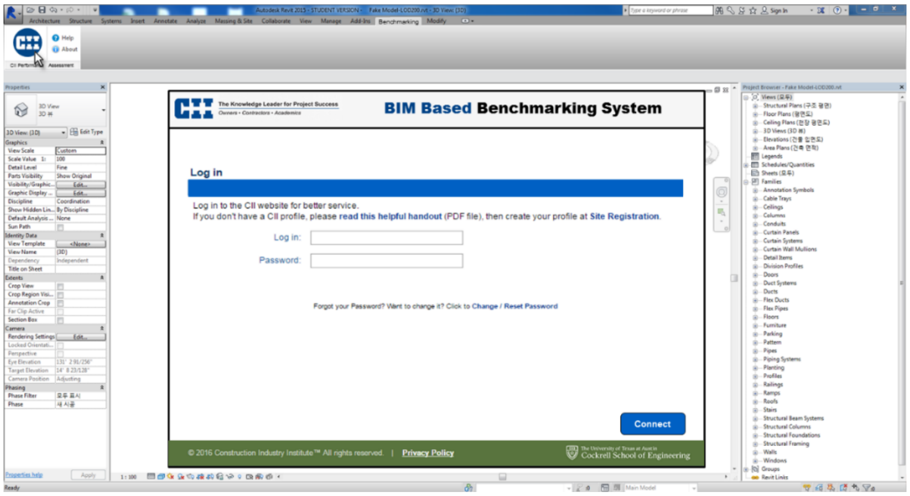


Figure 14: UI for the system log-in

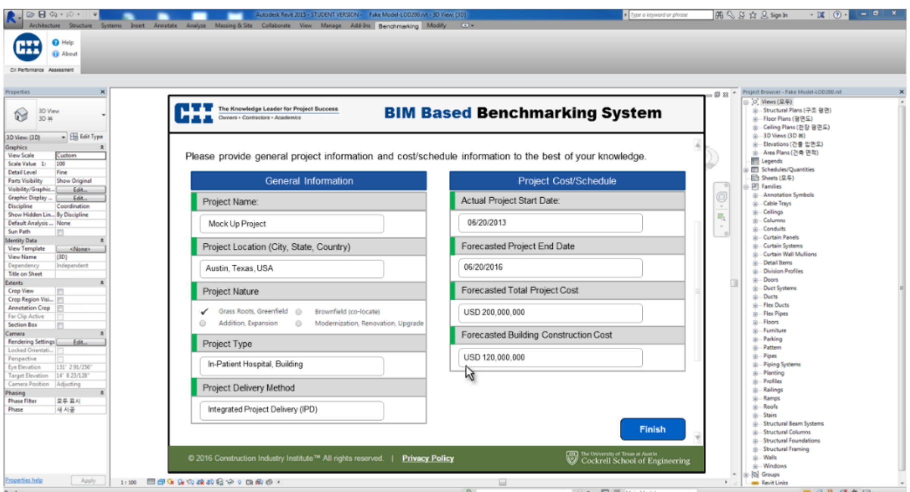


Figure 15: UI for general project information entry along with cost/schedule data

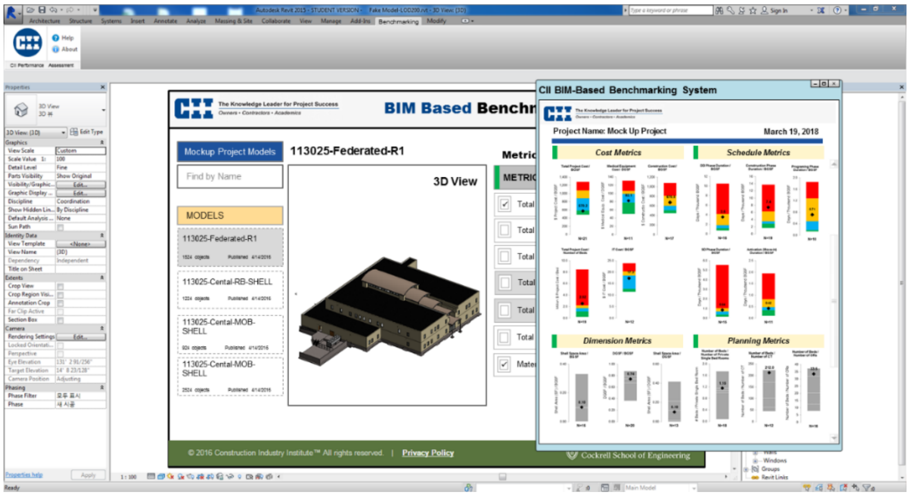


Figure 16: UI for reporting benchmarking outcomes

According to Figure 17, it is possible to conclude that the facility was over-estimated in terms of total project and medical equipment costs, and was planned with longer phase durations (i.e., detail design and construction) relative to its BGSF and DGSF in comparison with those of other in-patient hospitals. In contrast, given that both ratios of DGSF to BGSF and shell space area to DGSF fall around the median (50^{th} quartile), it is reasonable to judge that the ratios are within an allowable range considering those of industry peers. Finally, the results of the number of beds per the number of Computerized Tomography (CT) and ORs imply that too many beds were designed relative to the number of CTs and ORs, compared to those of other similar hospitals. It became clear that these benchmarking results can help project stakeholders to make informed decisions to establish targeted performance or determine baselines by providing reliable comparisons to industry peers.

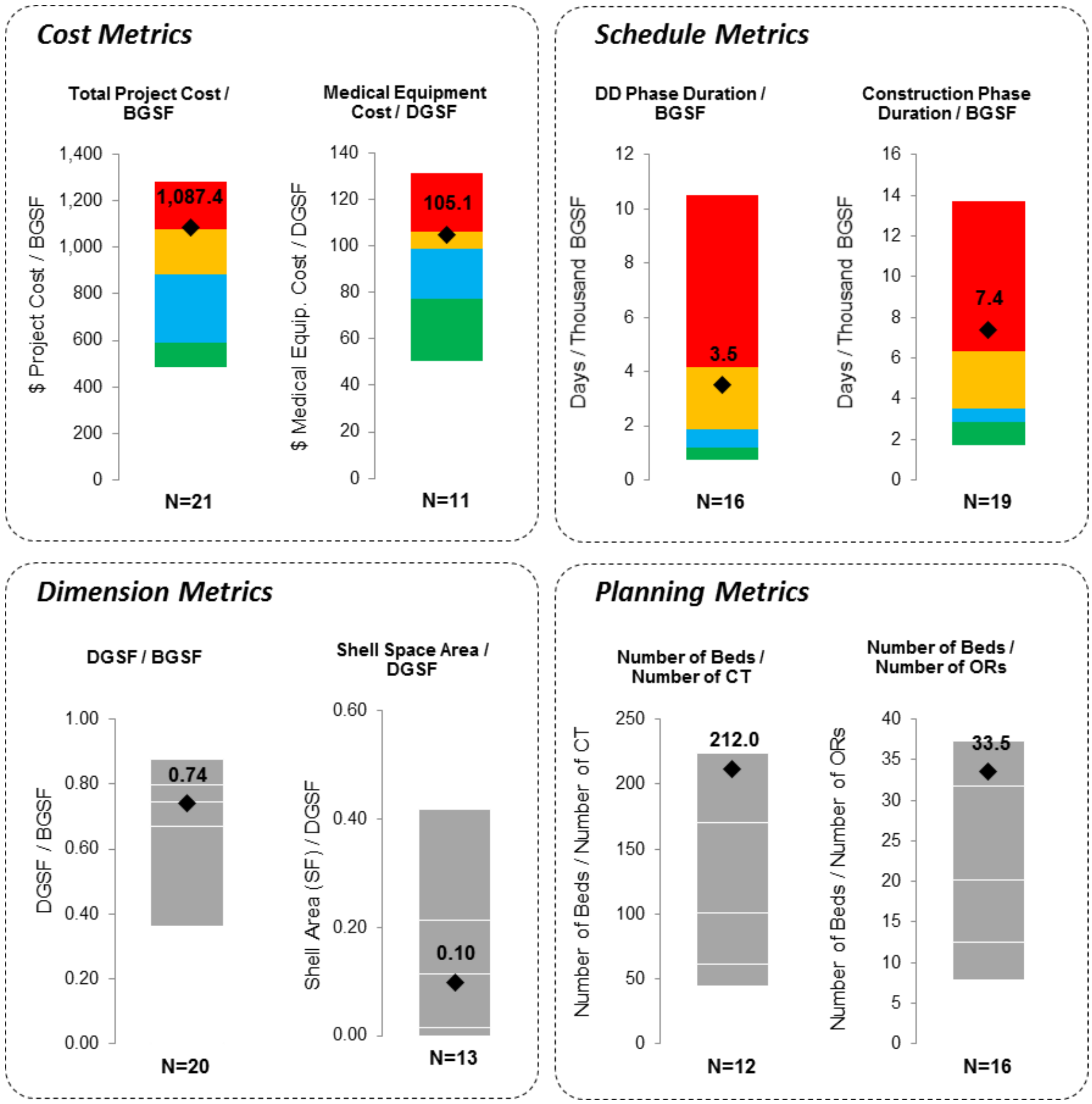


Figure 17: Metric comparisons using quartile charts

2.6. Discussion

It is expected that the benefits of BIM-based benchmarking could be significant. With minimized human intervention, users in healthcare projects can identify their competitiveness with respect to their peers based on a comprehensive list of metrics. With a BIM-benchmarking approach, healthcare project stakeholders can proactively implement performance analysis and benchmarking, thereby identifying their gaps with industry peers.

However, some issues and challenges associated with the envisioned BIM-based benchmarking approach are worthy of discussion. First and foremost, the main challenge that exists for developing a tool for use is that there are variations as to how differently BIM is produced. It is always necessary to assess whether the data extracted from the model provides an accurate representation of the actual products, considering the fact that reliable benchmarks cannot be generated with models containing inaccurate information. Moreover, the data-intensive and properly built models are required to fully exploit the benefits of the tool. In this regard, the modelers need to manage and develop BIM products considering the Level of Detail (LoD) and required information necessary for NHFBP. We envision that the BIM-based benchmarking can be implemented using the models produced in any phase, which would enable project stakeholders to proactively assess their project performance. However, it should be noted that higher LoD models contain more data that can be extracted, and adding more details leads to more accurate and reliable benchmarking outcomes.

Another issue related to BIM production and its contents, yet is worth noting, is that each project followed different naming conventions for naming elements; this is true for most data needed for NHFBP. Taking an operating room as an example, project A named it as “OPERATING ROOM”, while projects B and C, respectively, named it as “OR” and “Operating”. Existing BIM standards noted that naming conventions for all elements in BIM should be succinct, useful and descriptive (U.S. Department of Veterans Affairs 2010) in order to allow for easy identification and be easily understood, which facilitates data extraction from BIM. However, there is a lack of a consistent or formalized set of naming conventions applicable to design elements, spaces, materials produced in BIM. Several researchers proposed approaches to overcome the barrier concerning different naming conventions for the same elements; a name-based mapping by which a given string set is mapped to one of the standard names can be employed to match those to standard definitions (Lee et al. 2012), and ontology-based mapping which links a given string set with a standard one through ontological mapping (Kim et al. 2013b). However, this issue was outside the scope of this study.

The goal of this chapter is to explore feasibility for BIM-based benchmarking focusing on the NHFBP and establish its functional requirements, as a stepping-stone to achieve our overall vision. The results of this study indicate how well BIM can support data needed for NHFBP by analyzing BIM contents using real-world models of six healthcare projects, and also present essential functions of the envisioned tool. However, follow-up investigations are needed to realize our vision. First, the work for describing a high-level representation for processing data extracted from BIM into useful benchmarking data required for NHFBP is in currently being developed. The scope of this work is to detail how data can be systemically extracted from heterogeneous models, transformed into a proper format, and loaded into the NHFBP server. The quality of extracted BIM data is also explored in this study, followed by exploring the effect of the variance in BIM products on the data reliability by project phase. The development of a proof-of-concept for the BIM-based tool is ongoing so it will be reviewed to gauge the usefulness and feasibility of the system for healthcare facilities once developed. The authors recognize the importance of incorporating various NHFBP user perspectives in a proof-of-concept; hence, follow-up data collection to aimed at evaluating the tool will be conducted in a future study.

2.7. Conclusion

In the AEC industry, project benchmarking served as an effective technique, enabling an organization to establish improvement targets by explicitly identifying the gaps with their peers, and assisting in promoting changes for successful outcomes. While numerous benchmarking initiatives have been established in the AEC industry and recognized as meaningful tools for successful project delivery, they are still confronted with several shortfalls which impede users' active participation. One of the major issues is that the benchmarking entails considerable time and human effort to collect data and guarantee the quality of collected data.

Inspired by the recent technological advancement and prevalence of building information model (BIM) in the industry, this chapter introduces an envisioned approach that leverages BIM data and provides users with a more streamlined data collection and entry processes through a BIM-based benchmarking tool focusing on healthcare projects. Based on a comprehensive list of performance metrics tailored for healthcare facility, this chapter investigates the potential of BIM to feasibly support data needed for the metric calculations using real-world models. The result of analysis indicates that BIM, although supplemental data are required, can provide a considerable amount of data to measure NHFBP metrics (i.e., 82.8% of metrics are partially or completely measurable) so have high potential to replace current manual data collection and entry by users. This chapter, then, establishes a vision for a BIM-based benchmarking system by proposing functional requirements for such a tool, which is expected to streamline the benchmarking process needed for the implementation of NHFBP by reducing manual efforts while ensuring data security.

Although many research efforts have been made to automate diverse manual processes in the AEC industry, this study is one of the first studies which attempt to integrate BIM with project performance benchmarking practices. Thus, this research made a contribution to bridge the gap by conducting a feasibility study and establishing functional requirements which corroborates a smooth introduction of BIM to an existing benchmarking program (i.e., NHFBP). The findings of this study will provide a stepping-stone for accomplishing a BIM-based benchmarking tool for wide scale benchmarking implementation in the AEC industry.

Chapter 3 BIM-based benchmarking for healthcare projects: formalized representation for obtaining reliable benchmarking data from BIM models

In the healthcare industry, the BIM-based benchmarking approach was identified as an alternative method to improve the current laborious and error-prone benchmarking practice by reducing manual inputs required for data collection and entry. However, the current body of knowledge lacks a robust and consistent approach to obtain useful and reliable benchmarking data from heterogeneous models. To realize the BIM-based benchmarking, this chapter develops a formalized schema that transforms data stored in BIM models to obtain useful and reliable benchmarking data focusing on two neutral information models, Industry Foundation Classes (IFC) and Construction Operations Building Information Exchange (COBie). Focusing on a healthcare benchmarking program, it defines specific sets of transformation processes applicable to different groups of benchmarking data classified based on their attributes. Through the validation, it was found that using information embedded in models, the schema generated benchmarking data with a reasonable range of deviation from their actual values. However, it is expected that the accuracy of data will increase if models provide an accurate representation of the actual building. The proposed schema can allow for BIM-based benchmarking by establishing a consistent approach to obtain benchmarking data by leveraging BIM data, thereby reducing human interventions and leading to wide-scale adoption of benchmarking practice in the industry.

3.1. INTRODUCTION

Healthcare projects are characterized highly complex compared to other types of building projects due to technological sophistication, regulatory requirements, and a large number of users and workers, including, particularly, patients with identifiable vulnerabilities (Enache-Pommer et al. 2010; Kahn 2009). The healthcare organizations, thus, have adopted various strategies that add values to program, design, construct, and operate their capital (CII 2014). Among them, benchmarking has been perceived as an effective technique to improve project outcomes, which allows for identifying performance gaps with other peers and thus assist in promoting changes during the life cycle of projects. These days, performance assessment and benchmarking are considered critical components of the successful delivery of healthcare facilities (Choi et al. 2016; CII 2014).

As a unique benchmarking program focusing on healthcare project delivery ranging from programming to activation/move-in phases, the Construction Industry Institute (CII)'s National Healthcare Facility Benchmarking Program (NHFBP) has been widely adopted in the healthcare sector since its inception in 2012. It was designed to evaluate comprehensive metrics that address diverse project attributes concerned with cost, schedule, dimension, and planning of healthcare projects (Choi et al. 2017, 2018). Another feature of the program is that it is ported to a web-based platform equipped with an online data collection and reporting system that enables users to submit project data from actual projects while securing its database (Mulva and Dai 2009). Although the value of the program has been recognized by the participating organizations, some drawbacks have emerged with time. The major problem was related to the diversity and quantity of required project information. Collecting the benchmarking data and entering them into the survey instrument is a laborious and highly error-prone process that challenges the accuracy and reliability of benchmarking outcomes and also prevents incorporating it into their routine.

In the meantime, the utilization of Building Information Modeling (BIM) is a prevailing trend in the healthcare sector. BIM has transformed the process that buildings are designed and delivered in diverse ways, particularly when it comes to the construction of highly complex buildings such as healthcare facilities (Manning and Messner 2008; Merschbrock and Munkvold 2015). The data-richness nature of BIM allows for producing, storing, processing building information, and with this functionality of BIM, researchers began to discuss an opportunity to leverage BIM data for benchmarking by investigating its feasibility as well as requirements for realizing such a tool (Choi et al. 2018). The outcomes of the study reported that BIM standards and technologies could be leveraged to streamline the benchmarking practice (Choi et al. 2017, 2018) because a large amount of project information required for implementing the benchmarking program is potentially obtainable from BIM models. Although BIM-based benchmarking was identified as an alternative approach to streamline the current benchmarking process, previous studies lack a robust and consistent approach to obtain useful and reliable benchmarking data from heterogeneous models.

To fill the identified research gap, the goal of this study is to develop a formalized schema that represents the transformation processes of BIM data to obtain usable and reliable benchmarking data required for NHFBP. To accomplish this goal, this research investigates neutral information models tailored to building facilities, which are Industry Foundation Classes (IFC) and Construction Operations Building Information Exchange (COBie). The outcome of this chapter is a formalized schema that can be used to generate reliable benchmarking data by leveraging IFC and COBie models. The schema applied to NHFBP provides a consistent approach for populating necessary benchmarking data without interoperability issues, ultimately leading to streamlining manual benchmarking practices by reducing manual efforts associated with manual data collection and entry.

The remainder of this chapter is organized as follows. Section 3.2 presents the related works on benchmarking programs in the healthcare industry and NHFBP, along with BIM-based knowledge extraction in the construction industry. Sections 3.3 and 3.4 describe the research method and results of this study, respectively. The results are validated and discussed in Section 3.5, and finally, Section 3.6 concludes this research.

3.2. BACKGROUND RESEARCH

3.2.1 Benchmarking programs in the healthcare sector

Benchmarking provides healthcare organizations with a tool for collecting information to appreciate project performance from various perspectives, both within and outside of their organizations (Ettorchi-Tardy et al. 2012). Benchmarking in the healthcare sector made its first appearance in 1990 with the needs of the Joint Commission on Accreditation of Healthcare Organizations in the U.S., which defined it as an evaluation technique for monitoring the clinical, logistical, and managerial functions (Ettorchi-Tardy et al. 2012). Since then, several benchmarking frameworks have been established in the sector, such as the Performance Assessment Tool for Quality Improvement in Hospitals (PATH) designed by World Health Organization (WHO) (Groene et al. 2008) and the Health Care Quality Indicators (HCQI) initiated by the Organization for Economic Cooperation and Development (OECD) (Arah et al. 2006; Marshall et al. 2006), and the Facility Management benchmarking program operated by International Facility Management Association (IFMA) (IFMA 2013). However, the common goal of those efforts centered on improving the quality of healthcare service delivery, patient care, or the efficiency of facility operation, rather than facility performance ranging from programming to activation.

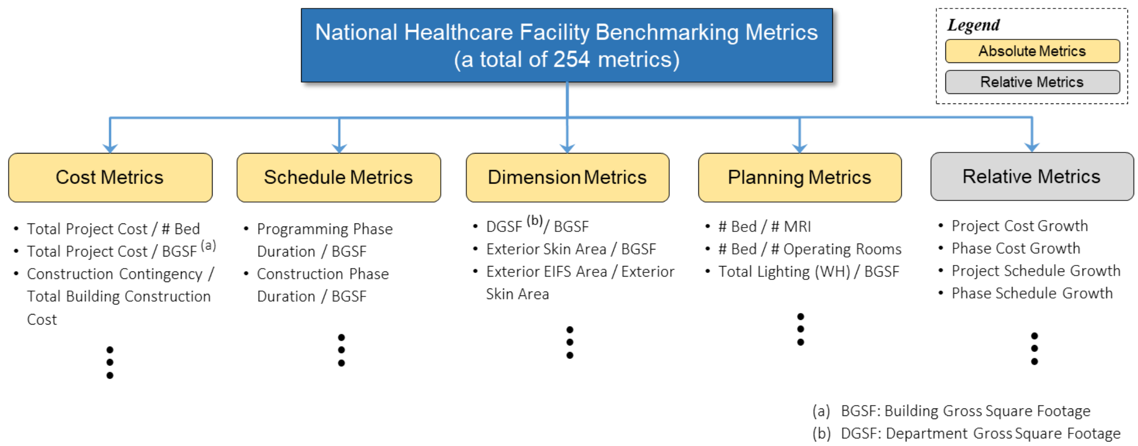


Figure 18: NHFBP metrics and categories

A research team of experts from academia and leading healthcare organizations developed the NHFBP to measure the performance of healthcare projects and compare the results against industry peers (CII 2014). During the development of the program, the research team identified and prioritized specific metrics to evaluate healthcare projects considering the key performance indicators (KPI). Principally, the metrics can be divided into two categories, i.e., absolute and relative metrics. The absolute metric represents, for example, ratios of costs (in dollars), durations (in days), building gross square footage (BGSF) to other costs, schedules, or dimensions in absolute terms (Hwang et al. 2010). The absolute metrics for NHFBP are relevant to project attributes of cost, schedule, dimension, and planning, which comprises 254 healthcare-specific metrics evaluated using project data collected from participants. Unlike the absolute metrics, the relative metrics are often represented as percentages or ratios of planned versus actual performance (CII 2014). Some relative metrics are also utilized in the program, which basically takes measurements of two same elements of project information; for instance, projected versus actual cost or schedule are evaluated in percentage. Examples of absolute and relative metrics adopted in NHFBP are presented in Figure 18. Note that a full list of metrics is provided in Appendix 1.

The NHFBP has been recognized as a meaningful tool enabling the process of quantifying the efficiency and effectiveness specific to the healthcare facilities (CII 2014). However, some shortcomings pertaining to its implementation have been identified, which impedes its wide adoption. The main issue is that the program, by its nature of comprehensiveness, requires a large amount of project information physically collected and submitted by participating organizations. Given a project stores and maintains those data in a fragmented manner with multiple formats, the time and efforts required to collect them are of major concern for participants. The quality of data is the cornerstone of generating reliable benchmarks. While a well-formulated and clear survey instrument can reduce the possibility of poor or incomplete data collection, there is always the potential for human error, particularly when a large dataset is submitted. As a way to help the participants to ensure compliance with the appropriateness of data to submit, formal training is provided on a regular basis. The training, in general, covers program definitions and instructions pertaining to detailed step-by-step guidance (Kang et al. 2012; Choi et al. 2016). It also requires considerable manual inputs from the NHFBP administrator (i.e., CII). Figure 19 illustrates a series of activities involved to implement the NHFBP at a high level, and three activities in grey are concerned with the aforementioned issues.

To mitigate this issue, researchers began looking into an approach to leverage data stored in BIM as a means of supporting necessary benchmarking data quickly and efficiently while diminishing the amount of time and human efforts. Examples of such studies include a BIM benchmarking application for evaluating the status of BIM utilization (Du et al. 2014; Liu et al. 2014), a BIM-based sustainability analysis tool for leadership in energy and environmental design (LEED) or energy consumption (Azhar et al. 2011; Wong and Kuan 2014). Those tools extract and aggregate data stored in BIM and report performance results automatically based on target metrics. The closest reference to this chapter is Choi et al. (2018), which focused on project performance benchmarking, particularly of healthcare projects. The study investigated the feasibility of BIM as a benchmarking data source focusing on healthcare projects and pointed out that healthcare BIM supports a substantial amount of data needed for NHFBP (Choi et al. 2018). The study classified all the required benchmarking data with regard to concepts, which generated separate groups of data. Although the study is meaningful as it laid a groundwork of a BIM-based benchmarking approach, it did not address how to leverage BIM to obtain usable and reliable benchmarking data, which is a limitation to be tackled to realize the approach.

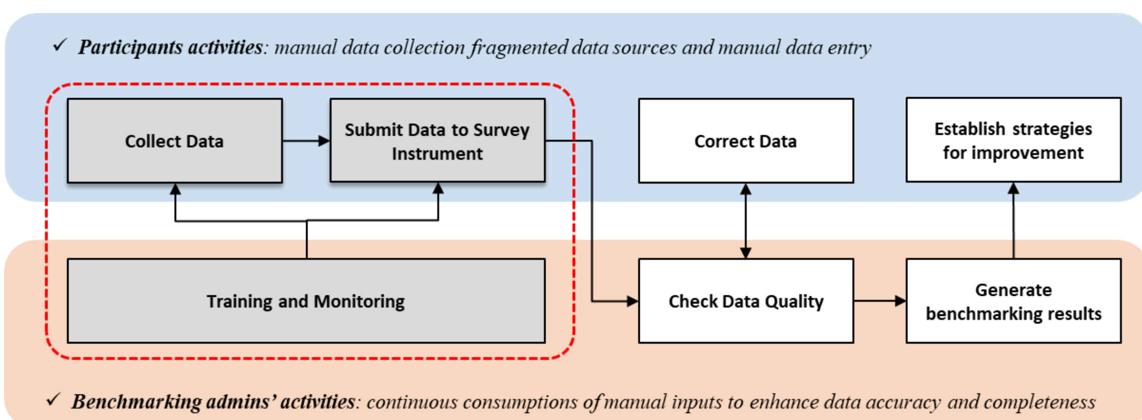


Figure 19: Schematic of the benchmarking process and main issues

3.2.2 Knowledge extraction from information models

The lack of integrated life-cycle information about facilities causes a significant amount of losses, which is estimated to cost $15.8 billion annually for U.S. capital facilities

(Gallaher et al. 2004). If the loss is adjusted to 2020 dollars with annually 2% inflation, it could be $21.7 billion. BIM has been used to allow for the information exchange through the life cycle of a facility, including the project execution phase (i.e., programming, design, and construction). Nowadays, IFC standards and COBie specifications are considered mature and widespread in the Architectural, Engineering, and Construction (AEC) and Facility Management (FM) domains because they enable BIM models to be structured in a neutral format allowing for product data to be exchanged between designers, suppliers, constructors, and operators (Patacas et al. 2015).

IFC is an international open data standard for BIM in order to improve information exchange by maximizing the semantic possibilities for the representation of the model (Hartmann et al. 2017; Yang and Ergan 2015). As an object-oriented file format, building information is assembled as a set of objects, each object containing attributes describing the object in the IFC schema. In addition to objects, the IFC schema supports a predefined set of rules, functions, or types used to gain data associated with a certain domain such as architecture or structural engineering (Theiler and Smarsly 2018). The IFC model is highly diverse in the object types that can be represented, and in IFC 4, 766 object classes represent physical and conceptual objects in the different domains (Hartmann et al. 2017). As a subset of the IFC model, COBie is based on the facilities handover model view definition (Hartmann et al. 2017; Patacas et al. 2015). It comprises 16 concepts relating to managed asset information including space and equipment but the key items to track for facility managers are (1) components (i.e., *COBie.Components*) that need operation/maintenance (O&M) and (2) spaces (i.e., *COBie.Space*) that need management (Yang and Ergan 2015). Currently, COBie can be represented using STEP, eXtensible Markup Language (XML) formats. By considering the users' inexperience and limited familiarity with the STEP, XML has become the common way to represent COBie

(Yalcinkaya and Singh 2015) as it enables COBie data to be organized through a series of data fields in a spreadsheet with multiple worksheets.

A large amount of data is circulated and generated in every project. The BIM implementation substantially increased the generation speed and amount of BIM-based data. A large amount of studies investigated information representation for effective knowledge and information retrieval and reasoning in the realm of the AEC industry; for example, a IFC-based querying mechanism for vulnerability assessment during building emergencies (Leite and Akinci 2012), a formalized knowledge representation schema for spatial conflict coordination of mechanical, electrical and plumbing (MEP) (Wang and Leite 2016), a customized data representation for generating different views of project information using data stored in product models (Reinhardt et al. 2005), and a data representation schema to semi-automated tower crane planning (Ji and Leite 2015). The consistent findings from those studies reported the tangible benefit of using BIM as model-based information repositories as an alternative approach to streamline manual and repetitive processes. However, to our knowledge, none of the research has investigated a formalized method that leverages information embedded in BIM models to support benchmarking data through a consistent and reliable approach.

3.3. RESEARCH APPROACH

BIM, as a data source for NHFBP, has a great potential of reducing manual inputs associated with collecting data and inputting such data into a survey instrument (Choi et al. 2017, 2018). However, a consistent approach to obtaining useful and reliable benchmarking data from BIM standards and specification is still lacking and deserve noteworthy attention to realize the BIM-based benchmarking. To overcome the observed gaps in the literature, this study aims to establish a formalized method to obtain useful and reliable benchmarking data by leveraging data stored in BIM. To accomplish our research goal, a two-step roadmap was undertaken.

The first step analyzed data items to obtain from information models with regard to their concept and characteristics (e.g., specific disciplines associated with the items, or type of measurement units to consider). The concepts related to space, building exterior system, bed, medical equipment, and building system are potentially available data stored in BIM as outlined in Choi et al. (2018). Building on the findings, this step classified the data belonging to each of the concepts by considering the attributes of the data, so that specific objects and properties embedded in the models can be linked with a group of similar data. Both IFC and COBie, as data sources, were explored to establish a consistent approach without barriers of an interoperability issue. To facilitate the analysis with consideration for the high complexities of IFC and COBie schemas (Hartmann et al. 2017), we collected five BIM models configured in IFC formats from on-going healthcare projects at the time of collecting the models now completed. A COBie data model (in XML format) was acquired from National Institute of Building Sciences (NIBS), which is an open file to the public, produced for a medical and dental clinic building at a location in the South-West United States (East 2011). By analyzing the contents embedded in the collected models, we investigated how to extract data in an efficient way while ensuring their reliability.

The next step developed a consistent approach to obtaining usable and reliable benchmarking data based on the findings from the first step. This approach was represented using a formalized schema that defines specific transformation processes (i.e., a series of operations) required to obtain different sets of benchmarking data classified on the basis of their attributes. Datasets obtained from IFC and COBie need to undergo appropriate transformation to be immediately usable for metric evaluations (Choi et al. 2018). This procedure involves consolidating or aggregating the subset of information extracted from the models. To that end, a unique library in which specific processing are defined, was developed by considering required operation routines. The data transformation process was, thus, represented using the library. When the schema was developed, new concepts possibly to be utilized for NHFBP metrics were also investigated and reflected in the schema for future expansion. To validate the proposed schema, factual project data are collected from two projects that donated IFC models. A comparative analysis was conducted mainly to evaluate the reliability of benchmarking data obtained from two IFC models through the schema. To populate the benchmarking data from the models based on the proposed schema, the IFC File Analyzer (IFA) V.2.71 developed by NIST, was used to generate XLS or CVS files from an IFC file (NIST 2019) and then a series of operations was implemented through Visual Basic for Application (VBA) in Microsoft Excel.

3.4. RESULTS

3.4.1 Classification of benchmarking data and model analyses

BIM supports data needed for measuring NHFBP metrics, and those data are classified into five concepts associated with space, bed, medical equipment (ME), building exterior system (BE), or building system (BS) (Choi et al. 2018). The data items included in each of the five concepts can be divided further by accounting for their attributes in the context of similarity. The similarity of data was evaluated by the measurement unit of the data, specific discipline related to the data, or the level of data specificity in consideration of an approach to capture relevant datasets from information models. The recursive data classification was, thus, implemented while investigating collected models so that each group of classified data can be transformed through an identical and consistent process to obtain data belonging to the corresponding group. This section summarizes the results of data classification by the concept as follows.

Table 5: Benchmarking data by category and sub-category

Category	**Sub-category**	**Benchmarking data**
Exterior System (EX)	• Total • Specific system	• Square Footage (SF) of total building skin • SF of each brick, Exterior Insulation and Finish System (EIFS), Glass Fiber Reinforced Concrete (GFRC), glass, metal panels (aluminum and steel), plaster, stone, and wood
Bed	• Total • Specific bed	• # of total beds • # of behavioral health beds, critical care beds, labor & delivery beds, medical and surgical beds, NICU basinets, contingency beds, and observation beds
Space	• Count	• # of exam rooms, observation rooms, operating rooms, private single patient rooms, semi-private single patient rooms, procedure room, and treatment bays
	• Area	• SF for atrium, building footprint, shell, roof gardens, bridge, site, building gross, and department gross
Medical equipment (ME)	• Object-based	• # of angiographies, C.T., heart catheterization, isotope treatment units, linear accelerators, mammography, MRI, PET, PET /CT, scintillation gamma cameras, SPECT /CT, and ultrasound
	• Space-based	• # of scanning rooms for all the medical equipment listed in “object-based” right above
Building system (BS)	• HVAC	• Capacity of boiler (HP), total fan supply (HP), total return/exhaust fan (HP), cooling capacity (tons), and heating capacity (MBH)
	• Electrical	• Cogeneration capacity (KW), total lighting (KW)

First, the space category includes data used to describe two different types of space data, which are the total number and total area of space measured by the units of count (EA) and square footage (SF), respectively. The number of specific rooms can be obtained from an IFC entity (i.e., *IfcSpace*) and a COBie concept (i.e., *COBie.Space*) by counting the number of objects representing the room of interest. However, for the SF of the rooms, a certain property (i.e., area) needs to be referred to, which is not required for the case of counting the number of rooms. In this regard, the space category in Table 5 was classified as two sub-categories, i.e., count and area. In addition, the data included in this category was divided into; 1) room space that represents a single room space, and 2) area space that groups rooms spaces (e.g., building gross area, department gross area, etc.). This separation based on area scheme can enhance the reliability of space data because the objects representing area space do not need to be counted, i.e., the SF matters only. Similarly, when the number of specific rooms is captured from data stored in the models, all the space objects representing area spaces can be ignored, vice versa.

Second, data items assigned to the ME category are concerned with counting the number of specific imaging equipment such as magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET). Counting the number of objects representing the equipment is a single unit of measurement for data included in this category. However, based on the analysis of collected models, ME objects are often not defined in the models; two out of five IFC models did not include objects indicating medical equipment needed for NHFBP. However, we also found from three remaining models that each of ME is located in a single room (i.e., one-to-one relationships between objects representing ME and room) as displayed in Figure 20. For instance, an MRI scanner is placed in an MRI scanning room, and the same is valid for other types of ME. This finding reveals that space objects and their properties can be leveraged to count the number of ME. In this regard, two sub-categories were created to accommodate different approaches: 1) “object-based” that counts the number of ME based on ME objects and their properties, and 2) “space-based” that counts the number based on space objects and their properties.

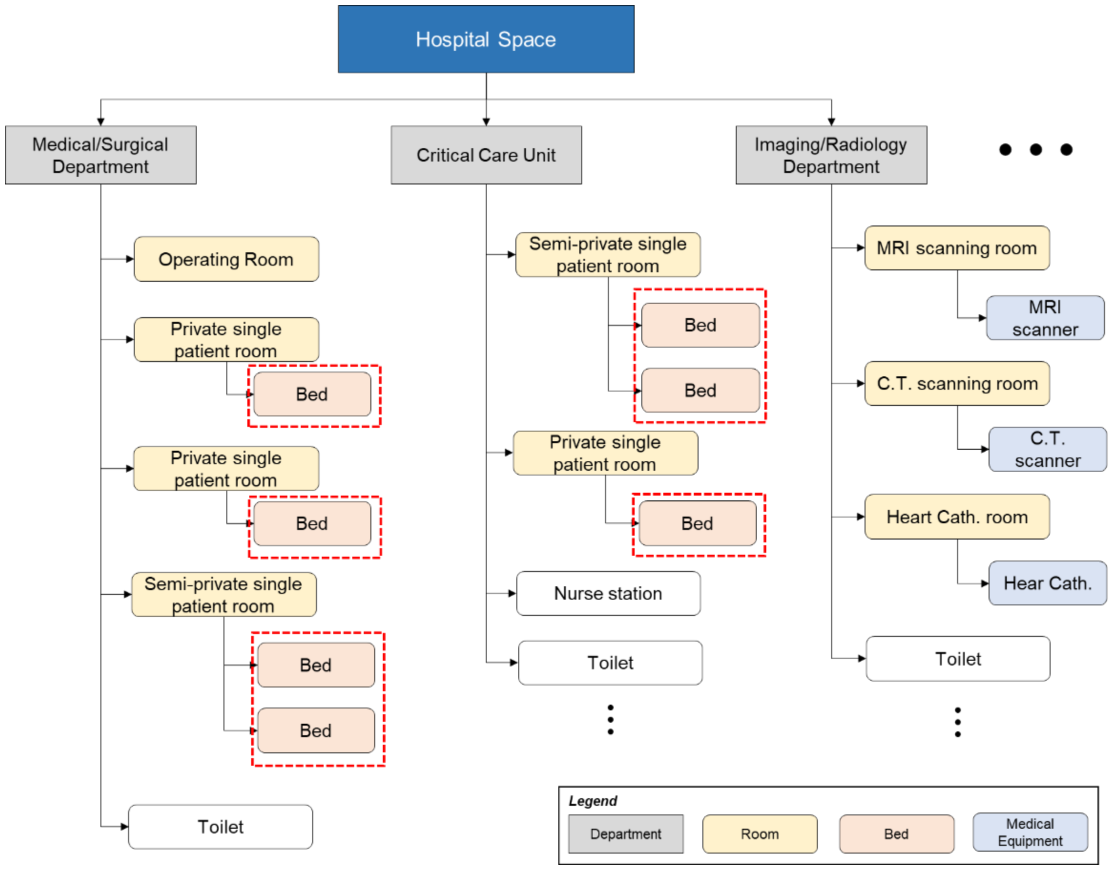


Figure 20: Schematic layout of bed and medical equipment by space

Third, all data items in the bed category are pertaining to counting the number of beds, but they can be split into sub-categories with consideration for the types of beds to be counted; one is associated with the numbers of specific beds, and another is total beds planned in the facility. The specific bed data is concerned with those placed in certain spaces or rooms, but the total bed focuses on the total number of beds located in the entire facility. Unlike the case of total beds, a property indicating the location of bed is, thus, required in order to count the number of specific beds. For instance, the number of critical care beds is interpreted as the number of beds located in the critical care unit that is one of many departments in hospital facilities, as shown in Figure 20. However, it was found from all the collected models that bed objects do not have the property indicating the department or room names where they are placed; instead, a property of room number was identically attached to the objects. Using the room number, a linkage among room, department, and bed objects can be made to leverage properties associated with one another since a room object includes a property indicating a department which the room belongs to. This linkage also allowed for counting the number of beds using space objects, provided that private single patient room has one bed although semi-private single patient room has two beds. Hence, it was concluded that the number of beds could be counted through two different approaches, similarly to the ME category, i.e., object-based and space-based methods.

Fourth, the BE category includes data representing the skin area (in SF) of a specific exterior finish system and total exterior skin area. The specific exterior finish system includes, for instance, exterior insulation and finish System (EIFS), glass fiber reinforced concrete (GFRC), glass, and metal panels; on the other hand, the total system addresses the total skin area of a facility without consideration for associated materials. In this regard, two sub-categories are created, which are the total and specific material. Provided that the exterior skin area excludes roof area by the NHFBP definition (CII 2014), all the building elements comprising the exterior system (e.g., wall, curtainwall, and window) need to be identified on the basis of their functions (interior or exterior) using one of the common property sets, i.e., *IsExternal* (buildingSMART 2019). In addition, to obtain the skin area for a specific system, the material property of the building elements is required together with their quantities in the unit of SF, which is not necessary for total skin area. For brevity, a detailed description of an approach to parse the SF of building elements, are not presented here. Instead, the reader is referred to IFC specifications (buildingSMART 2019) or other related research, e.g., (Kim et al. 2013a, 2015). It should be noted that COBie does not contain instances related to building elements in general, which indicates data in the BE category is not obtainable from the COBie specification (East and Carrasquillo-Mangual 2013).

Lastly, the BS category is pertaining to capacity-related data for different types of heating, ventilation, and air conditioning (HVAC) and electrical systems designed in the facility. Considering the disciplines associated with the data, two sub-categories separating mechanical and electrical data were created. To obtain capacity data for systems of interest, the entities or instances included in *IfcDistributionElement* and *COBie.Components* are explored (Lin et al. 2013; Patacas et al. 2015), along with their properties representing capacity or power. However, in BIM models, the objects representing mechanical, electrical, and plumbing (MEP) system are often generated with generic objects (i.e., library objects) rather than specific objects (i.e., manufacturer objects) that represent specific products (Choi et al. 2018), especially in the models constructed for visualization or clash detection purpose (McPartland 2019). The generic objects lack diverse properties of objects in models, which is needed for data items included in this category (e.g., properties of capacity or power). Thus, to obtain the data in the BS category from IFC models, relevant HVAC and electrical components are required to be designed with manufacturer objects with necessary properties. On the other hand, given the purpose of COBie, those data are well stored in a COBie sheet (i.e., *COBie.Components*) that inherit common attributes defined in *COBie.Type* (East and Carrasquillo-Mangual 2013).

3.4.2 Representation of data processing for benchmarking

Based on the findings from the classification of benchmarking data and model analysis, we developed a consistent approach to obtaining usable and reliable benchmarking data from IFC and COBie. This approach was represented using a formalized schema that defines specific transformation processes required to obtain different groups of benchmarking data classified on the basis of their attributes. As illustrated in Figure 21, five categories represent the concepts (or categories) that cover all the project information of interest, within the scope of this study. This schema is linked with transformation procedures tailored to a set of similar data indicated at the bottom of the leaf in the figure. Beyond the scope of this study, three extra categories are included in the schema for possible expansion by exploring the supplementary database and establishing additional performance metrics, which will be discussed in detail later in this section.

Table 6: Description of function library

Function	**Description**
Filtering (FT)	FT is a function that chooses a smaller and particular set of information of interest by excluding undesirable data, e.g., when the number of operating rooms is calculated using data stored in models, any room objects not representing the operating room are filtered out through a process of FT.
Counting (CT)	CT is a function that counts the occurrences of objects of interest, e.g., when the number of total beds is measured using data stored in the models, the totality of all objects representing a bed is evaluated through CT.
Associating (AS)	AS links an object to another through an identical property to add an additional property to the object, e.g., bed objects and space objects can be associated using a property restored in both objects.
Unit Converting (UC)	UC ensures that all the numeric values (e.g., linear, area, and volume) are in the imperial unit, e.g., when the metric unit is defined as a base unit in models, all the values are converted into imperial through conversion factors.
Aggregating (AG)	AG, as the last step of operation, sums the numeric values obtained from UC or counts the number of beds with consideration of room names.

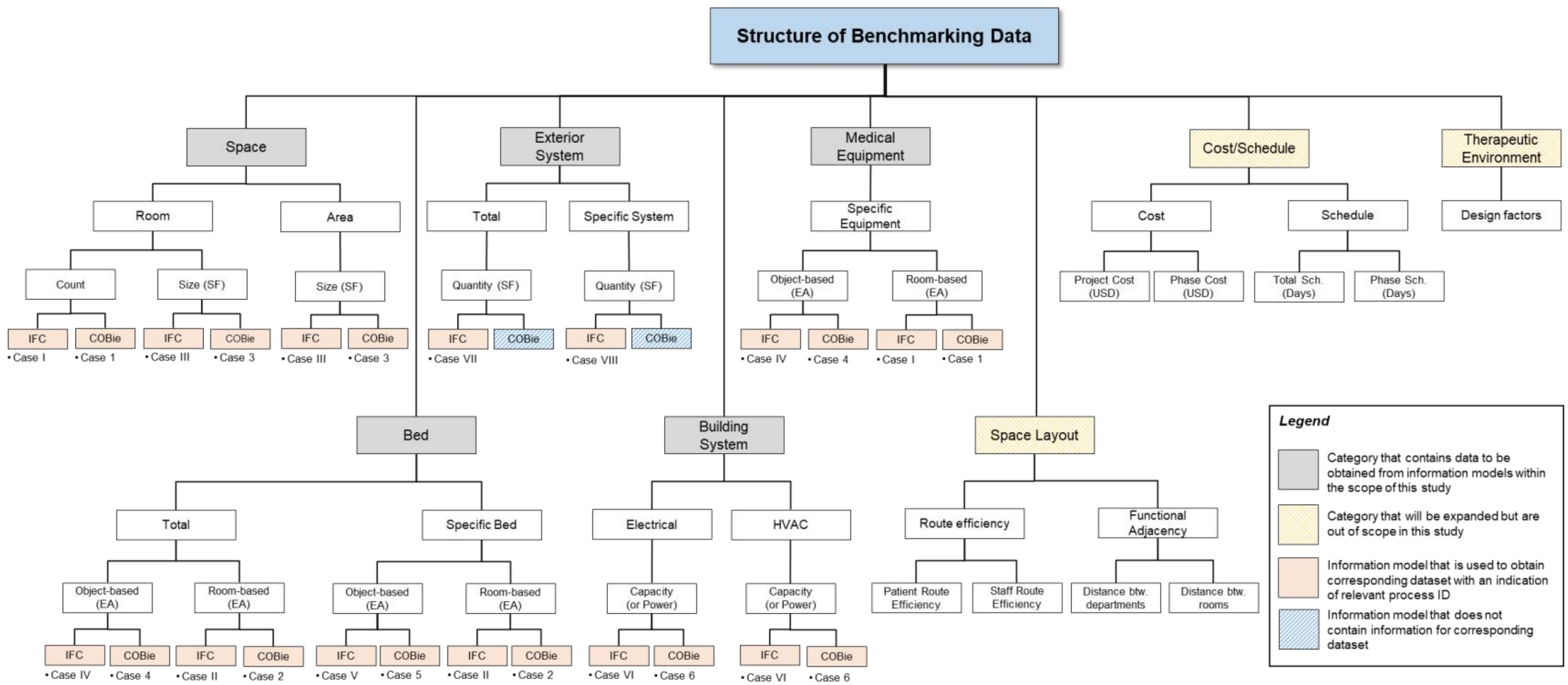


Figure 21: Representation schema for obtaining benchmarking data from IFC and COBie

While transforming the dataset extracted from models into usable benchmarking data, it was found that consolidating the datasets is performed through a series of specific operations that can be classified into five logical processes, i.e., filtering (FT), counting (CT), associating (AS), unit converting (UC), and aggregating (AG). The operations were described using a function library (as listed in Table 6) that is a collection of operation routines by defining a unique operation to be implemented to obtain useful data from a subset of information extracted from IFC and COBie. The procedure to transform data extracted from IFC and COBie into benchmarking data was represented using the function library, as shown in Figure 22. The procedure describes target objects or concepts as well as required properties, along with specific operations to be performed to obtain benchmarking data. The formalized transformation process, coupled with the representation schema, enables data stored in IFC and COBie to be extracted and consolidated in a consistent and reliable manner.

As shown in Figure 22, the number of rooms can be obtained through *Case I* (Roman numerals) for IFC and *Case 1* (Arabic numerals) for COBie, and the SF of rooms or areas are obtained through *Case III* for IFC and *Case 3* for COBie. For IFC, FT is implemented to separate areas and rooms, and then another FT is applied to find a space of interest, based on the name properties of the objects. In case of COBie, the name property of instances included in a space concept is scanned, and then any instances not representing a space of interest are removed. After that, the decision on area scheme (i.e., room or area) is made by associating the zone with the space concept as the zone concept addresses a group of spaces, i.e., area (East and Carrasquillo-Mangual 2013). Figure 23 illustrates how *Case III* is implemented to obtain the case of "total SF of operating rooms." Once any objects whose area scheme is "area" are filtered out from all space objects, the name property is scanned for the remaining objects. If the name is not matched with "operating room,” corresponding objects are filtered out again. The values in the “area” property of remaining objects are then scanned along with the unit of measurement. As the square meter (i.e., metric system) is used for the unit of area measurement, the values in the “area” property are converted into SF (i.e., imperial unit), and finally, the converted values are aggregated to obtain a single value for “total SF of operating rooms.”

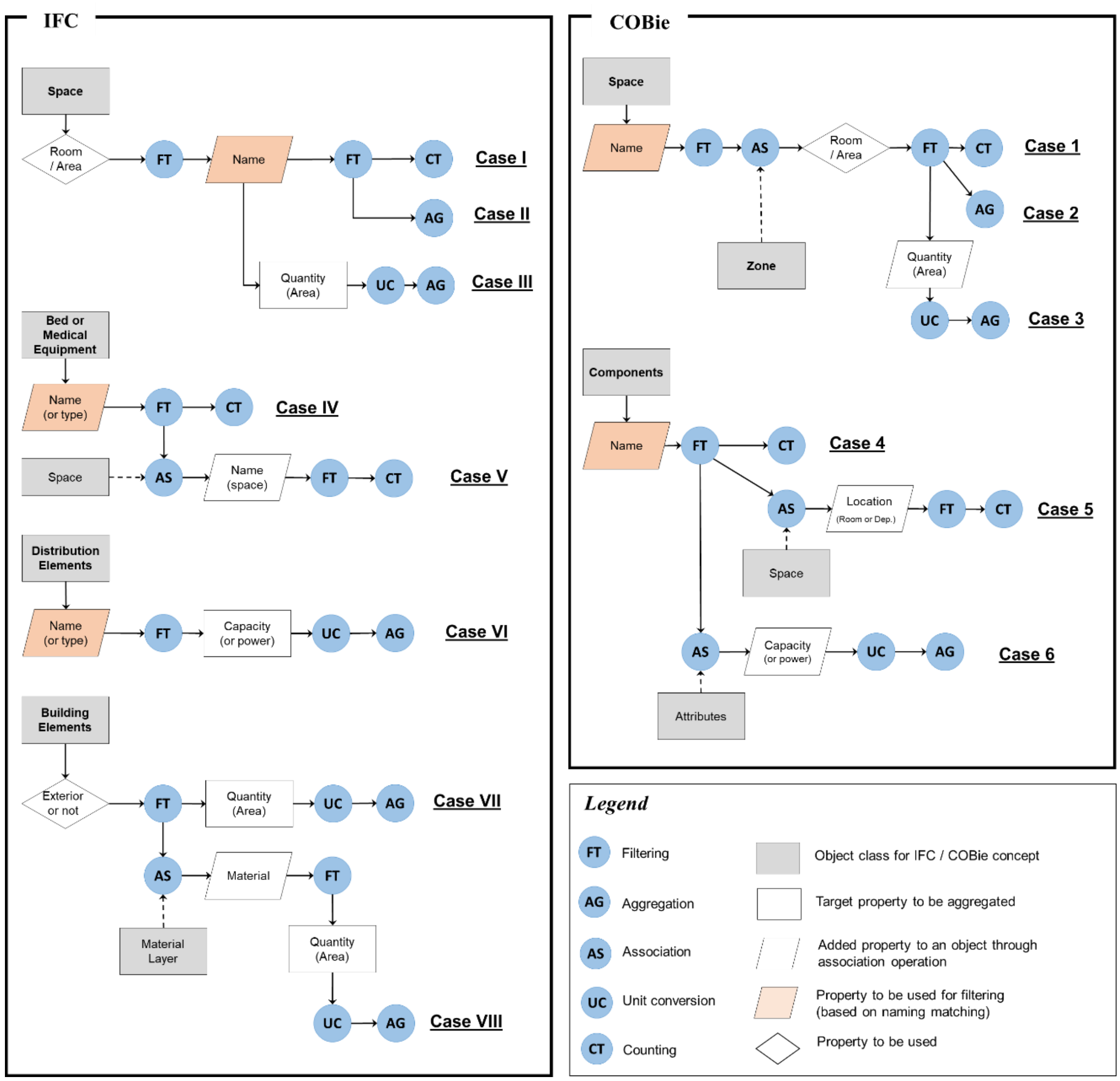


Figure 22: Representation of data transformation procedures

As previously discussed, data in both bed and ME categories can be obtained through either of object-based or room-based approaches, and both are concerned with counting the number of objects. Given this similarity, their transformation procedures for IFC were jointly represented, although they undergo different transformation processes depending on the counting approach. The total number of beds or equipment can be counted using *Case IV* when the object-based approach is used by counting the number of objects of interest after removing certain objects not relevant to ones we intend to extract. For the room-based approach, a one-to-one relationship between room and equipment allows the number of the equipment to be obtained by counting the number of rooms based on the “name” property of space objects (*Case I*); however, the numbers of total beds or specific beds counted through the room-based approach need the operation of AG by reflecting the number of beds based on the space name (*Case II*). To count the number of specific beds using bed objects, *Case V* can be implemented to associate bed objects with space objects as a way to determine the location of beds. Figure 24 presents how *Case V* is performed using the case of “the number of critical care beds”. As shown in the figure, after removing any objects not representing bed through FT, the remaining objects are associated with space objects through a property of “room number” which is identically embedded in both space and bed objects. Once removing the space objects not representing a critical care unit, the number of bed objects associated with the remaining space objects is counted to obtain the number of critical care beds using CT.

The same logic is applied to COBie using *COBie.Space* through *Cases 1* to *3*. The component concept of COBie, as the central piece of the asset register, comprises individual instances of the products such as an item of equipment, light fittings, furniture, or valves (physical objects) (East and Carrasquillo-Mangual 2013), which can support both bed and ME data, along with BS data through *Cases 4* to *6*. For BS data, *Case VI* and *Case*

6 are applied to both HVAC and electrical for IFC and COBie, respectively. The "name" or "type" property of device or equipment is used to identify objects of interest, and the "capacity" (or power) property of such objects are aggregated after ensuring the unit is in the imperial system. In case of COBie, the attribute concept that stores expanded properties mainly for equipment or device listed in the component concept can be associated so as to provide needed information (East and Carrasquillo-Mangual 2013).

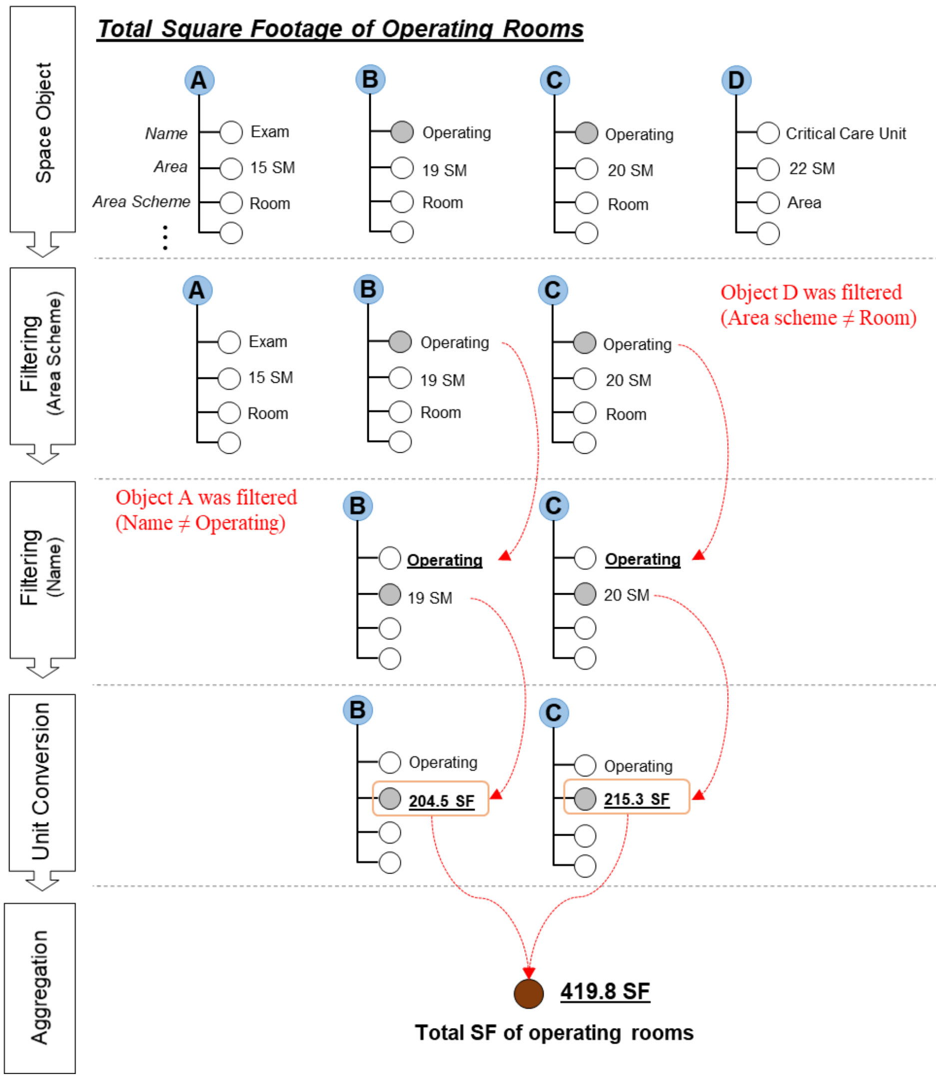


Figure 23: Data transformation for the area of operating rooms (Case III)

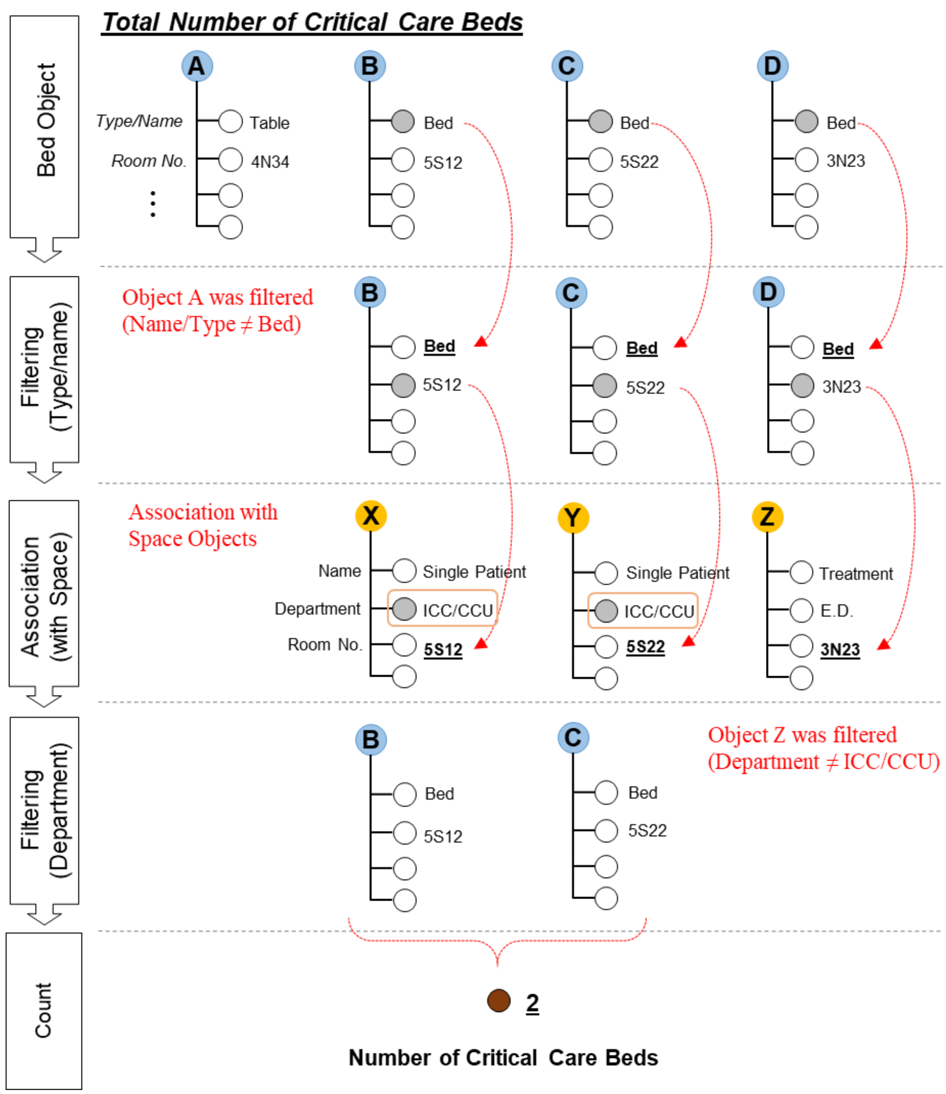


Figure 24: Data transformation for the number of critical care beds (Case V)

For BS data, two different series of operations (*Cases VII* and *VIII*) are implemented depending on their sub-categories (total vs. specific) for IFC; however, the data in this category is not potentially available in COBie as previously mentioned. Both *Cases VII* and *VIII* start from selecting exterior objects from building elements through FT.

The “area” (quantity) property of the exterior objects are then aggregated after unit conversion for total skin area through *Case VII*, and for specific system, material layer objects can be associated with the exterior objects to link the material of the objects and then FT can be applied to remove any objects that are not relevant to materials of interest.

As displayed in Figure 21, some extra categories are included for possible expansion of the schema, i.e., cost/schedule, space layout, and therapeutic environment. First, cost and schedule data identified as “not available” data in BIM models according to the previous study that analyzed multiple real world BIM models collected from healthcare projects (Choi et al. 2018). Although current information models do not contain this information, an external database for cost and schedule management is linked with the models, which enables cost and schedule data to be obtainable. Second, previous studies found several constructs that are relevant to the performance of healthcare projects, although those were not utilized for NHFBP. Examples of these studies include space layout (Lee and Kim 2014; Sanguinetti et al. 2012) and therapeutic environment (Griff 2012; Mourshed and Zhao 2012). The efficiency of space layout has been considered critical because staff or patient walking distance or building access and circulation are largely influenced by functional adjacencies of space. In particular, BIM has provided a great benefit in the analysis of space layout by automating route simulation and analysis (Eastman et al. 2009; Lee et al. 2016). Another category added was the therapeutic environment which has been emphasized by previous research as a way to improve patient outcomes, safety, and quality of care, and to enhance staff satisfaction and effectiveness. To that end, researchers found that appropriate lighting, access to daylight, noise reduction, or right-sized patient room, can reduce measurable positive effects on patients' clinical outcomes and staff effectiveness (Ulrich et al. 2008, 2012). Those factors also have great potential to be simulated or analyzed using BIM data. However, an important step to address additional categories in benchmarking practice is to establish key performance indicators (KPI) which represent key aspects of the project activity (Horta et al. 2010). The KPI development is under consideration for the two categories (i.e., space layout and therapeutic environment), associated data items will be defined, and accordingly, the existing sets of metrics will be expanded by incorporating extra metrics.

3.5. VALIDATION AND DISCUSSION

The proposed representation schema was validated by comparing data values obtained through the schema using IFC models against the factual data manually submitted through the survey instrument. We collected benchmarking data from two healthcare projects that donated two IFC models for this research, enabling a comparative analysis using data acquired from two sources. Those projects were selected for validation because as large-scale inpatient hospitals, their models incorporated various types of information (e.g., medical equipment, space, and bed) that allows the comparison to be conducted with a comprehensive dataset.

Table 7 presents an excerpt of data values obtained from the proposed schema and those manually submitted by projects. The accuracy indicating the discrepancies between two data on the basis of relative ratio in percentage was also provided in the table. The degree of discrepancies between data obtained from two sources differs by category; data belonging to the ME category were exactly identical for two sources, implying that data obtained using the proposed schema generated accurate data. Data included in space and bed showed slight differences between data two sources. The largest variation was identified from the number of medical/surgical beds for Project A (for bed category) and from the SF of warm shells for Project B (for space category). In particular, no space objects representing warm shells reside in the model for Project B, which generated the SF of warm shells as zero, although it was reported that there are some areas for warm shells in reality.

Compared to data in other categories, the high degree of discrepancies was discovered from those belonging to BE and BS categories. The SF of total building skin is close to 10% of the difference between two sources; however, the accuracies of the other four data in the two categories range from 0% to 180% without any ones being close to 100%. The reasons for the observed differences between data obtained from two sources may be attributable to the fact that the contents of IFC models do not accurately represent the as-built facility. Both models we used for comparisons were created during the design phase and susceptible to changes during construction or commissioning phases, provided that construction projects are prone to a high degree of design change (Sun and Meng 2009). We also noticed that there are relatively large differences in data included in BE categories (i.e., EIFS and GFRC) for both projects. Although the quantities of EIFS were obtained from two models, it was reported that those were not used in actual. Conversely, the quantity of GFRC was not acquired from Project B while it was used for an exterior system. This fact indicates possible design change occurred after producing the model that populated the benchmarking data in this study. Another possible factor causing the difference is concerned with using generic objects or missing objects/properties, particularly for objects representing data included in the BS category. As shown in the table, no capacity data for fan or lighting were obtained from Project B because the capacities were not defined in the light fixture entities. This was also valid for the case of total fan supply. Even worse, no objects representing fan were embedded in the model for Project A. In this regard, it is always necessary to evaluate whether the data stored in information models represent actual products with the properties required (Choi et al. 2018). Reliable benchmarking data cannot be obtained from models that include inaccurate or missing information. Moreover, there might have been some errors in the factual data submitted from the project, which generated different values in data acquired from the schema using the models. As aforementioned, manual data collection is error-prone, given that data are collected from fragmented sources in different formats. As a large amount of the collected data should be manually entered into the survey instrument, it is always possible to have typing errors or mistakes. For instance, slight differences in the numbers of critical care beds and labor & delivery beds for Project B or in BGSF for Project A can be attributable to the design change, but there is a possibility of errors associated manual data collection and entry, given the minimal degree of deviance between data obtained from two sources.

A limitation of this study is that validating the accuracy of data produced using the proposed schema is challenging as models reflecting as-built facilities are not available; however, we identified that although a large degree of discrepancies exist for the data associated with BS and BE categories, data included in other categories were obtained from models with a reasonable range of deviation from actual values using the proposed schema. If the objects designed in the virtual environment provides an accurate representation of the actual building (e.g., as-built models), the accuracy of data is expected to increase. To confirm this, a follow-up model collection is planned to aim at comparing the data generated by the proposed schema using as-built models with factual data, as a path forward. Currently, the investigation of new metrics well suited for healthcare projects is ongoing, focusing on additional concepts included in the schema for future expansion. Once the new metrics are established, the identical methodology implemented in this study can be conducted so as to obtain necessary benchmarking data from BIM models in a consistent way.

Table 7: Excerpt of comparison between data collected from a project & data extracted using models through the schema

				Project A			Project B		
Type	Subtype	Data	Unit	Manual (a)	Schema (b)	Accuracy (a/b)	Manual (a)	Schema (b)	Accuracy (a/b)
Bed	Specific	# Behavioral Health Beds	EA	0	0	100.0%	0	0	100.0%
Bed	Specific	# Critical Care Beds	EA	20	22	90.9%	30	29	103.4%
Bed	Specific	# Labor & Delivery Beds	EA	5	5	100.0%	10	9	111.1%
Bed	Specific	# Med and Surg Beds	EA	92	115	80.0%	128	129	99.2%
Bed	Specific	# of Contingency Beds	EA	0	0	100.0%	0	0	100.0%
Bed	Total	# Total Licensed Beds	EA	149	148	100.7%	216	215	100.5%
BE	Total	Total Building Envelope	SF	126,670	114,675	110.5%	140,500	124,792	112.6%
BE	Specific	EIFS	SF	0	2,488	0.0%	0	985	0.0%
BE	Specific	GFRC	SF	80,717	45,024	179.3%	74,201	0	0.0%
BS	Electrical	Total lighting	KW	277	155	178.7%	650	0	0.0%
BS	HVAC	Total fan supply	HP	855	0	0.0%	740	0	0.0%
ME	Specific	# Angiography	EA	0	0	100.0%	0	0	100.0%
ME	Specific	# C.T.	EA	2	2	100.0%	2	2	100.0%
ME	Specific	# Isotope Treatment Units	EA	0	0	100.0%	0	0	100.0%
ME	Specific	# Linear Accelerators	EA	0	0	100.0%	0	0	100.0%
ME	Specific	# Mammography	EA	0	0	100.0%	0	0	100.0%
ME	Specific	# MRI	EA	1	1	100.0%	1	1	100.0%
Space	Area	BGSF	SF	280,665	287,952	97.5%	434,993	435,868	99.8%
Space	Area	Building Footprint Area	SF	49,000	48,754	100.5%	83,920	86,452	97.1%
Space	Area	DGSF	SF	192,305	220,120	87.4%	316,717	342,342	92.5%
Space	Room	# Private Single bedrooms	EA	133	127	104.7%	216	215	100.5%
Space	Room	# Procedure rooms	EA	1	1	100.0%	1	1	100.0%
Space	Room	# Semi - Private single bedrooms	EA	8	8	100.0%	0	0	100.0%
Space	Room	Warm Shell Space Size	SF	1,029	1,029	100.0%	0	815	0.0%

Note: (a) is the data manually submitted by projects; (b) is the data obtained through the proposed schema and transformation procedures; and (a/b) is the relative ratio (in percentage) by dividing values in (a) by those in (b).

3.6. CONCLUSION

With the widespread implementation of Building Information Modeling (BIM), an important discussion in the benchmarking domain involves the transition toward automated implementation that aims to reduce the amount of human efforts involved in benchmarking practice. BIM has great potential to feasibly support project data needed for a healthcare benchmarking program, which is a great opportunity to streamline the current practice. However, it is still unclear how to obtain useful and reliable benchmarking data from BIM models. In response, this study developed a formalized schema that can be used to obtain reliable benchmarking data using information stored in BIM models. Specifically, the schema defines specific transformation processes applicable to different sets of benchmarking data required for NHFBP, focusing on IFC and COBie so as to establish a consistent approach to process BIM data without the barriers of interoperability issues. The proposed schema is expected to allow for BIM-based benchmarking, thereby reducing human interventions and leading to wide-scale adoption of benchmarking practice in the industry by streamlining the current manual benchmarking practice.

The schema was validated by comparing data values obtained through the schema using two IFC models with the factual data manually submitted by the projects donated the IFC models. Through the validation, it was found that the schema generated relatively accurate benchmarking data included bed, space, and ME categories while there was a large discrepancy in data concerned with BS and BE categories. The observed deviance in the data values was explained by the inaccurate representation of data or missing data in the studied model as well as the possibility of typing errors in the manually submitted data. It is expected that the accuracy of data will increase if models provide an accurate representation of the actual building. As a path forward, a follow-up study will be conducted to validate the proposed schema using as-built models and to compare the data with actual data. Future work also includes the expansion of the schema by accommodating new benchmarking data based on metric development suited for the healthcare facility.

Chapter 4 A novel approach to capture similarity in capital project benchmarking: an application to healthcare facilities

Project performance benchmarking as a technique for continuous improvement allows organizations to identify performance gaps with industry peers. For credible project benchmarking, the like-to-like project comparison is a prerequisite to set realistic targets for improvement, especially when a heterogeneous sample of healthcare projects is compared to another. However, the current method for determining the groups of similar projects relies on an ad-hoc technique that can lead to suboptimal target settings for improvement. To address the issue, this research proposes a novel approach to capture similarity for capital project benchmarking focusing on healthcare facilities by leveraging Classification and Regression Trees (CART). The data collected from a total of 89 healthcare projects were used to construct the trees by selecting a set of critical and flexible features that are closely associated with two metrics representing cost and schedule performance of healthcare projects. The effectiveness of results derived from the proposed method was validated through statistical methods and comparative analysis. The proposed method allows for more targeted performance comparisons by capturing similarity using flexible sets of meaningful features, which reduces the search space of determining a group of similar projects. The new approach is, thus, expected to help organizations gain better insights into their relative performance position when benchmarking their capital projects.

4.1. INTRODUCTION

Benchmarking is vital for any organization seeking to continuously improve its project management as it allows for cross-project learning (Farris et al. 2006). The construction industry institute (CII) describes benchmarking as a systematic process of measuring an organization's performance against recognized leaders for the purpose of determining best practices that lead to superior performance when adapted and utilized (CII 2019). Cross-project learning can be achieved by comparing a project's performance in the context of similar projects (Mulva and Dai 2009) in order to give benchmarking users information about the relative position of their projects using performance metrics (IPA 2019).

However, benchmarking practice presents diverse challenges, primarily due to the reigning paradigm of project uniqueness (Choi et al. 2016). As pointed out by (Newell 2004), "the more a project is perceived as unique, the less likely are teams to try and learn from others." Accordingly, the determination of a set of similar projects is essential for cross-project learning through benchmarking so that observed performance information can be compared on a like-for-like basis while bringing confidence in the benchmarking outcomes (Rodríguez-Déniz and Voltes-Dorta 2014). In this regard, one of the crucial components for reliable benchmarking is finding groups of similar projects, which would be referred in this chapter as *project grouping*.

To date, benchmarking research in the construction domain has mainly focused on the development of key performance indicators (KPI) (Swarup et al. 2011; Yeung et al. 2009a; Yun et al. 2016), establishment of a benchmarking system (Choi et al. 2015; Lee et al. 2016; Sebastian and van Berlo 2010), and identification of factors impacting project performance (Choi et al. 2019; Eriksson and Westerberg 2011; Korkmaz et al. 2010; Love 2002). However, the existing literature has paid little attention to developing a robust and systematic methodology for capturing project similarity, instead of relying on ad-hoc techniques. Although the existing approach is widely implemented, it has certain limitations that can be improved upon so as to enable organizations to gain better insights into their performance position. This study describes these limitations in the next section.

Recently, data mining techniques have been widely used to assist project stakeholders in complex decision making by allowing for the production of prediction models using historical data (Choi and Lee 2010). Data mining has been contributed towards construction project management domain such as predicting the outcomes of safety (Tixier et al. 2016; Goh and Chua 2013), dispute (Chou and Lin 2013), information system (Soibelman and Kim 2002), procurement scheduling (Kim et al. 2008; Poh et al. 2018) using diverse techniques including neural networks, decision trees, support vector machine, K-nearest neighbors, logistic regressions, or random forests. Among different algorithms, decision trees have been broadly used due to their transparency in describing the rules that lead to a classification/prediction (Liu et al. 2017; Mistikoglu et al. 2015; Park et al. 2016). As they are arranged in a hierarchical tree-like structure and are simple to understand and interpret, they can be well-suited for cases in which we need the model to be flexible in group extraction and the model to provide insights into the reason for a particular decision (Mistikoglu et al. 2015). With these benefits, decision trees have been successfully applied for assessment of energy consumption by allowing for estimations of desired performance targets using historical data (Park et al. 2016; Liu et al. 2017).

The objective of this research is to develop a systematic project grouping method that partitions heterogeneous healthcare projects into groups of similar ones using a set of critical and flexible features that are closely associated with performance metrics. In conjunction with various data mining techniques, we investigated different modeling methodologies applicable for project grouping in the initial phase of this study, which includes clustering techniques and data envelopment analysis. Clustering, as a segmentation model, is a process of splitting a dataset into similar clusters where data within each group are similar to each other and distinctive across clusters (Fan and Xiao 2017; Kim et al. 2008); however, as unsupervised modeling methods, it does not reflect the relationship between input and target variables. As an alternative methodology, data envelopment analysis assesses the comparative efficiency of projects that have multiple features and target variables by comparing the performance of each project to its similar ones (Farris et al. 2006; Vitner et al. 2006). However, a major disadvantage of the analysis was that it has a limited capability to handle a small dataset having multiple categorical data simultaneously, particularly nominal variables having numerous categories. Therefore, decision trees were selected after considering a range of possible solutions.

The analysis was conducted using a total of 89 project data collected from a healthcare specific benchmarking program, namely national healthcare facility benchmarking program (NHFBP) that is designed to benchmark healthcare project using a comprehensive set of healthcare specific metrics (Choi et al. 2018). To illustrate the proposed approach, this study focused on two metrics as target variables that represent cost and schedule performance of healthcare projects, which are total project cost (TPC) per building gross square footage (BGSF) and construction phase duration (CPD) per BGSF. This chapter uses regression trees (RTs) to predict the values of metrics. However, rather than focusing on the actual prediction of the metric value, this analysis is interested in the rules created by the tree to reach the different nodes (or groups) of projects down the tree. The project groups generated using the RT-based method, are expected to enable organizations to gain better insights into their relative performance position and to make better decisions for improving their project outcomes.

4.2. BACKGROUND

This section introduces NHFBP focusing on its project grouping approach, along with the review of the methods adopted for other benchmarking research as a motivation of this study. As a point of departure, past research applied data mining techniques in the construction domain was reviewed.

4.2.1 Existing approach to capture similarity of healthcare projects

As a healthcare-specific benchmarking program, the NHFBP is designed to benchmark 254 metrics related to the project cost, schedule, planning, and facility dimension based on a total of 173 data points (Choi et al. 2018). The survey asks for not only performance related data, but also requires general project information and specific practices implemented during project delivery for project analysis (Mulva and Dai 2009). Those data are collected through various types of questions using radio button (e.g., yes/no), checkbox (e.g., check all that apply), or open box, and they are stored in the database in categorical or continuous data formats. Since its inception in 2012, a total of 89 healthcare projects have submitted performance data through the survey instrument, and those data went through a rigorous data validation process to confirm the quality and reliability of provided data (Choi et al. 2017).

Currently, the NHFBP determines the similarity of projects using the attributes listed in Table 8, along with possible values for each attribute. The four attributes have been regarded as critical to characterize building facilities and well applied to a variety of previous benchmarking studies for project grouping (Choi et al. 2015; Hwang et al. 2008; Lee et al. 2005). Examples of these studies include several benchmarking programs managed by the Construction Industry Institute, including a pharmaceutical specific benchmarking and a phase-based benchmarking program (Hwang et al. 2008), and a BIM cloud score that is a benchmarking tool, aiming at evaluating a project's BIM implementation level against industry peers (Du et al. 2014). The latter was designed to compare projects based on the combination of industry sector, project delivery method, and the range of total project cost. Also, a phase-based performance benchmarking program, as a tool capable of benchmarking across different sectors on a phase basis, used the combination of industry sector, phase, and project type for project grouping (Choi et al. 2015, 2016; Yun et al. 2016). According to the literature in the realm of project performance benchmarking, it was found that sets of pre-defined project attributes are widely used for project grouping across all metrics, although there were slight discrepancies in project attributes used.

Table 8: Project attributes used to for NHFBP project grouping

Attributes	**Project type (PT)**	**Sub-type (ST)**	**Project nature (PN)**	**Cost category (CC)**
Categories	IPH	Primary care	Greenfield	Less than USD 5MM
		Secondary care	Brownfield	USD 5-15MM
		Tertiary care	Modernization /	USD 15-50MM
		Quaternary care	Renovation	USD 50-100MM
		Critical access	Addition/Expansion	USD 100-500MM
	MOB	Business use		More than USD 500MM
		Institutional use		

Note. IPH and MOB stand for Inpatient hospital building and medical office building, respectively.

Furthermore, one important consideration for project grouping is a confidentiality policy, which must ensure that data are published as aggregated results precluding identification of individual projects or organizations (Chanmeka et al. 2012; Hwang et al. 2008; Lee et al. 2005). The minimum number of data points for a reporting organization reporting are defined in the organization's confidentiality policy. The policy adopted in NHFBP notes that the distributions of metric scores presented to users must reflect the aggregate of at least ten projects submitted by at least three separate organizations (hereafter 10-3 policy) (CII 2014). Based on the 10-3 policy and four attributes utilized for project grouping, an approach to partition project into similar ones follows sequential *if-then* logic illustrated in Figure 25. If the 10-3 policy is not met with a set of projects that match all categories of four attributes, then the pool of projects is expanded by ignoring one of the attributes at a time in the order of *cost category*, *project nature*, *sub-type*, and *project type*. This process is repeated until the number of grouped projects satisfies the policy.

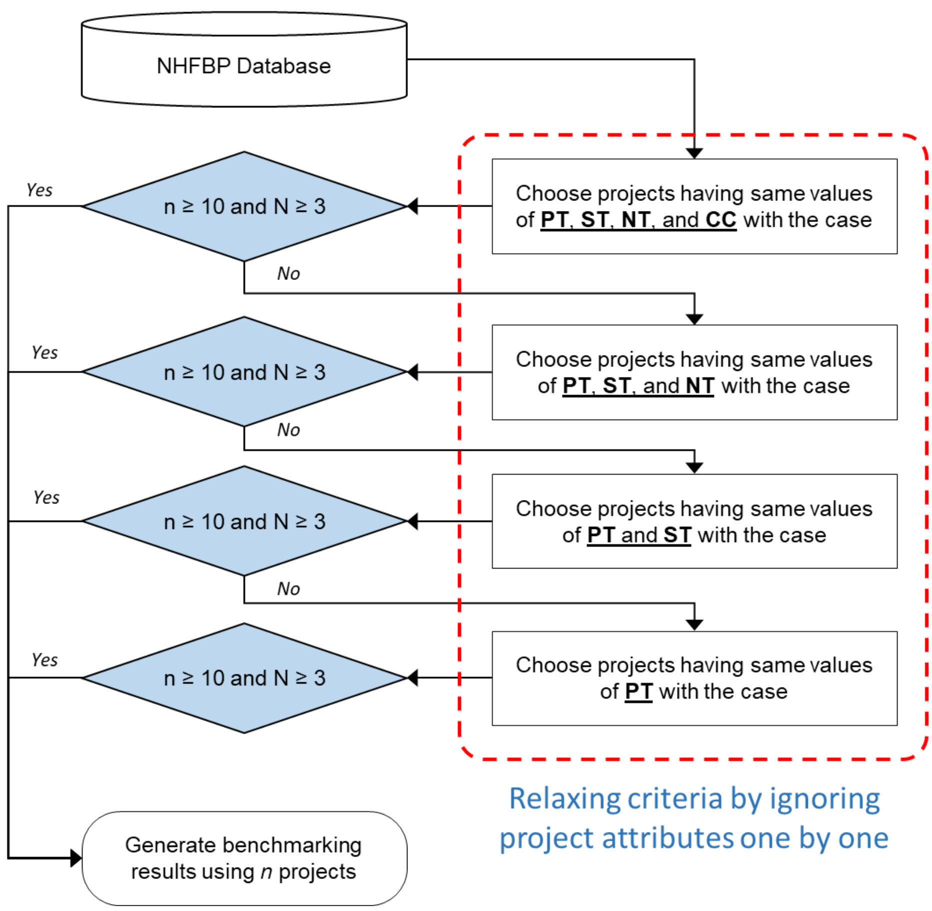


Figure 25: Schematic of project grouping method adopted for NHFBP

Given the 10-3 policy and four attributes utilized for the determination of project similarity with the number of projects collected from NHFBP thus far, one can identify a possible limitation of the current project grouping algorithm. First, for a small number of projects (a total of 89 healthcare projects), it is difficult to accommodate all four attributes considering the number of categories for each attribute. In reality, *cost category* is disregarded in most cases, and *project nature* is often ignored when a group of similar projects is determined for comparison. It is, thus, questionable if a set of grouped projects using one or two attributes is really similar enough for performance comparison across projects. Moreover, various metrics representing different aspects of performance are employed for NHFBP. Although the variability of the metric values may be influenced by different sets of attributes, a fixed set of four attributes is consistently used across all of 254 metrics. Provided that each metric is unique and might be associated with different project features, the fixed set of pre-selected features used in the current approach fails to capture differences in metrics' nature. The variation in each of NHFBP metrics may be accounted for different attributes that are more relevant to a corresponding metric, instead of the four fixed attributes. The level of similarities among grouped projects can be increased by using a flexible set of attributes that better explains the variation of target metrics.

4.2.2 Classification techniques and decision tree

The primary goal of data mining is to detect and predict qualitative and quantitative patterns in data, leading to new information and knowledge (Weng and Meng 2011). It has been used in diverse scientific domains, and many different methods and algorithms have been employed to perform predictive modeling in the construction management area. Some examples include predicting injury characteristics using large historical injury reports based on random forests and stochastic gradient tree boosting (Tixier et al. 2016), predicting heating and cooling loads of residential buildings based on random forests (Tsanas and Xifara 2012), predicting the occurrence and severity of accidents using occupational safety and health management system data based on neural networks (Goh and Chua 2013), classifying dispute propensity of public-private partnership projects using support vector machines (Chou and Lin 2013), and predicting appropriate retaining wall system using hundreds of excavation cases based on logistic regressions (Choi and Lee 2010).

Compared to other data mining techniques, the decision trees show excellent potential for analyzing and classifying project performance data in a human-interpretable format. The techniques such as neural networks, K-nearest neighbors, support vector machines, or random forests lack human-interpretability. This black-box characteristic makes it difficult for the modeler to validate and justify the final results (Choi and Lee 2010; Zhou et al. 2016). On the other hand, the decision trees have an advantage over other data mining techniques in that the method produces rules that are explicitly represented as a set of human-interpretable decision rules (Mistikoglu et al. 2015). The decision tree typically consists of a root node that is split into a number of branches, and a chain (thread) is formed through child nodes at successive tree levels. The child nodes are further subdivided into branches, and the thread continues until an end node (leaf) is reached at the bottom of the tree. The unique path from the root node to a leaf is a rule (decision rule), which is the human-interpretable representation of the information provided on any given thread (Mistikoglu et al. 2015). The root node contains the entire data set, and the tree grows by partitioning data at the parent nodes into smaller child nodes. To figure out which group a data point belongs to, one can start at the root node of the tree and trace a path down the tree according to the features of the data point (Weng and Meng 2011).

There are numerous decision tree algorithms, such as chi-squared automatic interaction detection (CHAID) (Kass 1980), classification and regression trees (CART) (Breiman et al. 1984), C5.0 (Ville 2006), quick, unbiased and efficient statistical tree (QUEST) (Loh and Shin 1997), and classification rule with unbiased interaction selection and estimation (CRUISE) (Kim and Loh 2001). These algorithms basically differ in the splitting criteria or method they use when splitting a parent node into child nodes, in the number of splits into child nodes (i.e., binary or multiple nodes), in the tree pruning approach, and in the format of target variable (i.e., continuous or categorical data) (Pham 2006; Ville 2006). See Table 9 for further detail.

Table 9: Characteristics of different decision tree algorithms

Algorithms	**Splitting criteria**	**Splitting approach**	**Tree size control** [a]	**Output variable**
CHAID	Chi-square or ANOVA [b]	Multiple	C	Categorical
CART	Gini index or Least Square Deviation (LSD) impurities	Binary	A	Both [c]
C4.5/C5.0	Information gain and entropy	Multiple	B	Both
QUEST	Chi-square or ANOVA	Binary	A	Categorical
CRUISE	Chi-square or ANOVA	Multiple	A	Categorical

Note: [a] A = cost-complexity pruning approach, B = pessimistic error pruning approach, and C = stopping rules-based approach; [b] ANOVA = Analysis of variance; and [c] both indicates categorical and continuous variables.

Among diverse decision tree algorithms, classification and regression tree (CART) has been widely conducted with a high level of accuracy and performance for predicting problems in the construction engineering area (Pakgohar et al. 2011; Park et al. 2011; Salimi et al. 2017; Tran and Carmichael 2013). As a widely used tree-based model, the CART makes no distributional assumptions on any dependent or independent variable and can be used with the dependent variable being either qualitative or quantitative (Loh 2014). Its simple binary tree structure offers excellent interpretability, and thus it serves as a powerful exploratory tool for understanding the underlying structure in the data (Pham 2006).

4.3. RESEARCH METHODOLOGY

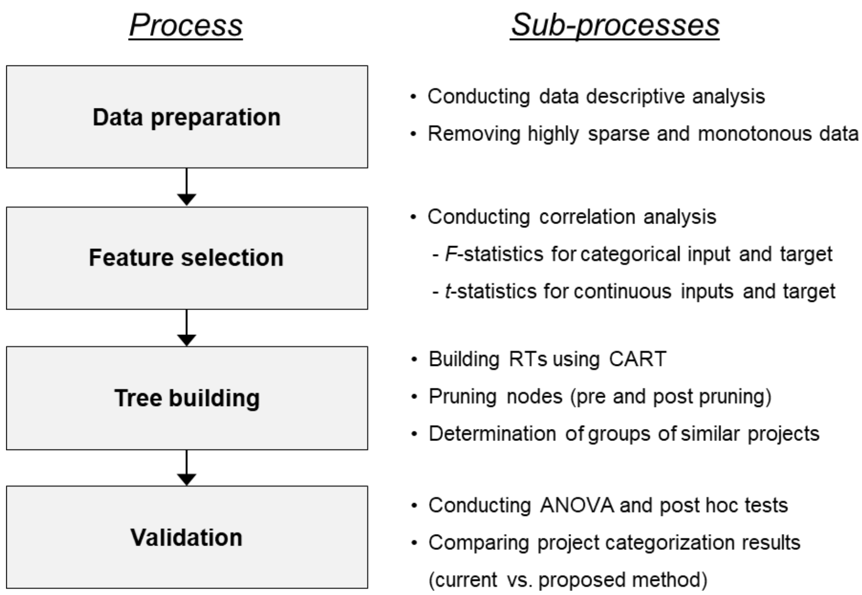


Figure 26: Research Process

Benchmarking results arising from the ad-hoc determination of similar projects may lead to misinterpretation of relative project performance positions, thereby possibly negatively affecting stakeholders' decisions. The overall goal of this study is to develop a methodology that systematically captures project similarity and then generates sets of similar projects grouped using features that are closely related to each of the metrics. The construction of trees is conducted using the CART algorithm that produces the nodes representing the different groups of projects based on metric scores in an interpretable manner. To achieve this goal, the research reported in this chapter was conducted in four phases as shown in Figure 26: (1) data preparation, (2) feature selection, (3) building decision trees, and (4) validation. Detailed explanations on four phases and employed methods are provided as follows.

4.3.1 Data preparation

This study uses a total of 89 project data submitted by 11 healthcare organizations in the United States. Although previous studies tend to prioritize certain sets of project attributes to group projects for benchmarking, this research considers all project characteristics available in NHFBP as potential attributes usable for project grouping tasks. Given that hundreds of variables are collected for each project in the NHFBP, this step aims to remove variables that do not add useful information ahead of the feature selection step. Due to a variety of information is asked through the NHFBP survey instrument, its database contains some variables with a large amount of missing values. Despite the validation process to ensure the quality of submitted data (CII 2014), missing values are a prevalent issue in project databases because some questions are not applicable to projects in certain circumstances, and some projects are unwilling to share critical information with someone outside of their organizations. In general, data mining algorithms deal very poorly with highly sparse data (Soibelman and Kim 2002) and, therefore, variables with missing value across more than 50% of the projects in the database were removed from the initial dataset.

Moreover, the database maintains some categorical variables, particularly binary questions, that have all records falling into the same category across all projects, which do not contribute to the variance of target value at all. Those variables were also discarded. Finally, we removed the dataset submitted by projects that do not have metric scores of either TPC/BGSF or CPD/BGSF. Through this step, it was determined that a total of 75 variables are candidate features associated with 85 projects submitted by 11 organizations for TPC/BGSF, and 63 projects submitted by 8 organizations for CPD/BGSF.

4.3.2 Feature selection

Feature subset selection is the process of identifying and removing as much irrelevant and redundant information as possible (Esmaeili and Gabor 2011). It reduces the dimensionality of the data and may allow learning algorithms to operate faster and more effectively (Poh et al. 2018). The feature selection also allows for a more compact, easily interpreted representation of the target concept (Ebrahimi et al. 2009). To narrow down the selection features from the 75 candidate features chosen in the previous section, a feature selection approach was applied to discover a set of features that have a strong correlation with each of the two targets.

We considered one feature at a time to determine how each alone explains each of the metrics. The degree of correlation for each variable is, then, calculated as $(1–p)$, where p is the p value of the appropriate test of association or relationship between the candidate features and the target metric. The association test for continuous target variables differs from the test for categorical variables. In our study, as metric scores are continuous, p values based on the t distribution of the Pearson correlation coefficient, were used when features are continuous; otherwise, a one-way ANOVA method was implemented for each input variable (Ebrahimi et al. 2009). Among the valid inputs, ones with $(1-p) > 0.90$ were selected as features for building RTs, and the selected inputs are provided in Table 10. A total of 22 and 16 features were selected for TPC/BGSF and CPD/BGSF, respectively.

Table 10: Selected features based on the relationship with target (α > 0.9)

Rank	Features	Data type [a]	Categories or unit	α or (1-*p*)
For TPC/BGSF				
1	Building code (Title 24)	B	Yes, No	1.000
2	Shared incentive used in the primary contract	B	Yes, No	1.000
3	Location	B	California, Others	1.000
4	Openbook contractual agreement	B	Yes, No	1.000
5	Principal contracting method for construction	B	Lump Sum, Cost	1.000
6	Project complexity [b]	O	Factors 1, 2, 3, and 4	1.000
7	Building code (IBC)	B	Yes, No	1.000
8	Total project cost	C	U.S. Dollars	0.999
9	Principal contracting method for	B	Lump Sum, Cost	0.999
10	Seismic zone	N	Zones 0, 1, 2, 3, and 4	0.997
11	Union site construction workforce	N	Union, Non-Union,	0.997
12	Principal contracting method for design	B	Lump Sum, Cost	0.996
13	Principal contracting method for	B	Lump Sum, Cost	0.992
14	Project subtype	N	*See Table 2 for*	0.986
15	Project type	B	MOB, IPH	0.984
16	Part of a medical campus	B	Yes, No	0.981
17	On site field GC staff size	C	FTE (full time	0.969
18	Existence of helistop facility	B	Yes, No	0.962
19	Project nature	N	*See Table 2 for*	0.954
20	LEED [c] certified or certifiable	B	Yes, No	0.944
21	Use of BIM	B	Yes, No	0.936
22	Principal contracting method for	B	Lump Sum, Cost	0.906
For CPD/BGSF				
1	Number of floors	C	EA	0.999
2	BGSF	C	Square foot	0.999
3	Number of elevators	C	EA	0.999
4	Number of basement levels	C	EA	0.998
5	Total site size (inside project limit line)	C	Square foot	0.998
6	Construction phase duration	C	Days	0.998
7	Total project cost	C	U.S. Dollars	0.993
8	Building footprint size	C	Square foot	0.962
9	Number of operation rooms	C	EA	0.951
10	Environmental remediation required	B	Yes, No	0.947
11	Principal contracting method for design	B	Lump Sum, Cost	0.938
12	On site field GC staff size	C	FTE (full time	0.923
13	Use of BIM	B	Yes, No	0.920
14	Building code (IBC)	B	Yes, No	0.919
15	Replacement of an existing building	B	Yes, No	0.909
16	Full EIS [d] required	B	Yes, No	0.901

Note. [a] B, O, N, and C represent binary, ordinal, nominal, and continuous variables, respectively; [b] factors 1 and 4 represents the lowest and highest difficulty, respectively; [c] LEED = leadership in energy and environmental design; and [d] EIS = environmental impact statement.

4.3.3 Building Regression Trees

We deployed the CART algorithm to predict the scores of TPC/BGSF and CPD/BGSF using a pool of 22 and 16 features selected in the previous section. As discussed above, the goal is to capture the set of attributes that are used to split projects down the tree eventually leading to the groups at the leaves of the tree. Constructing a tree revolves around three components which are 1) selection of the splits, 2) decision of when to declare a leaf node or to continue splitting it (i.e., pruning the tree), and 3) assignment of each leaf node to a class (Tran and Carmichael 2013). As a tree growing method, the CART selects each split of a node so that the observations in each of the descendant nodes are purer than those in the parent node, and it considers the least squares deviations (LSD) for a continuous dependent variable (Breiman et al. 1984). When CART grows a tree using metric scores that is continuous, splitting variable and split point are determined by minimizing the mean square error (MSE), and the node impurity is measured by Equation (1):

$$i(m) = \frac{1}{N_m}\sum_{i}[y_i - \bar{y}(m)]^2 \qquad Eq.(1)$$

, where $\bar{y}(m)$ is the mean of the metric scores at node m. The best split (j, t) is thus determined by solving Equation (2):

$$\min_{j,t}\left\{\sum_{i\in m_L}[y_i - \bar{y}(m_L)]^2 + \sum_{i\in m_R}[y_i - \bar{y}(m_R)]^2\right\} \qquad Eq.(2)$$

, where m_L is the left descendent node given by $x_j < t$ and m_R is for the right descendent node.

Two different tree-pruning techniques were employed when growing a tree: pre-pruning and post-pruning. As a pre-pruning approach that stops growing the tree by establishing stopping rules (Esposito et al. 1997), the minimum records (i.e., metric scores of projects) in the parent of leaf node was defined as ten projects as an absolute value to satisfy the 10-3 policy. To avoid overfitting by reducing subtrees (or bottom-level splits) and thus constructing "right-sized" tree (Li 2006), the difference in error estimation (i.e., the one standard error rule) was applied so that the difference between the errors in the pruned tree and the full tree is not more than one standard error (Quinlan 1999). Another post-pruning consideration was employed to ensure that the number of organizations associated with records in a leaf is not less than three as a way to comply with the 10-3 policy. This process was started from the leaf node of which the number of records in a parent node is not less than ten, as defined in the pre-pruning approach. If the replacement of a parent node with a leaf node would lead to an increase in the number of records and organizations, then the node was pruned. We used the SPSS Modeler 18.2.1 to complete our work.

4.3.4 Validation

We validated the results of the project grouping derived from RT analysis in three ways. First, in order to ensure the reliability of the results, the analysis of variance (ANOVA) method was carried out to test the differences in means across the leaf nodes. As a statistical model using a F-test, the ANOVA provides a statistical test of whether the means of multiple groups are equal or not. The outcomes of the test can imply how each group (i.e., records in a node) is discriminated well against other groups in terms of mean metric scores. Provided that ANOVA results do not identify which particular differences between pairs of leaves are significant, post hoc test was conducted after the ANOVA test.

If ANOVA indicates statistical significance, subsequent multiple comparisons were made using Tukey's honestly significant difference (Tukey's HSD) post hoc test to determine differences between pairs of groups.

Second, to confirm the effectiveness of the proposed method, a comparative analysis was conducted to compare and contrast the existing project grouping method and the proposed one: 1) by comparing the number of features used to classify projects in the context of similarity and 2) by comparing the root mean squared error (RMSE) and mean absolute error (MAE) derived from two methods, using the following formulas:

$$MAE = \frac{1}{N}\sum|y_i - \hat{y}_i|, \quad RMSE = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{N}}$$

, where y_i is actual metric score, $\hat{y}_i$ is the mean metric scores of projects in a similar group (i.e., estimated values of metric score in a project group), and N is total number of projects. Based on the RMSE and MAE, the degree of similarity in metric scores of projects grouped through the proposed method was compared against those grouped through the existing approach.

Lastly, we discussed the advantages of the proposed project grouping method over the existing approach by comparing the quality of attributes utilized in two methods and potential benchmarking outcomes derived from the methods through subjective assessment.

4.4. RESULTS

This section presents how the CART algorithm can be employed to generate groups of similar projects using candidate features (Table 10) for two representative metrics.

4.4.1 Determination of similar projects using RTs

Following the methodology described in Section 3, RTs were constructed as illustrated in Figure 27 and Figure 28. The number of grouped projects and organizations submitting the project data are provided for each node, along with mean and standard deviation of projects' metric scores included at each node. Figure 27 displays the RT for TPC/BGSF, which generated nine groups based on six features, i.e., use of Title 24 (T24), staff size of onsite general contractor (GC), *sub-type*, *project nature*, TPC, and project complexity (PC). Title 24, as a collection of energy standards adopted and implemented by the California Energy Commission, addresses the efficiency of energy consumption and preserve indoor/outdoor environmental quality (California Energy Commission (CEC) 2019). The PC indicates the level of difficulty for this project, compared to other healthcare projects by considering several factors such as restriction of site access or working condition, and project location (CII 2014). A higher factor represents the greater difficulty.

It can be seen in Figure 3 that the first level feature is T24; the second level features are GC and *sub-type*; the third level features are *project nature* and TPC; and the fourth and the lowest level features are PC and GC. In the figure, leaf nodes were color-coded in blue or orange to represent whether records included in the node meet the 10-3 policy. The blue nodes (i.e., groups A to D) include 10 or more similar projects submitted at least three organizations while those in orange (i.e., nodes 5, 8, 10, 11, and 15) do not meet the policy. The projects included in the nodes in orange need to be compared to all project included in its parent node. Using the tree, one can identify the association between selected features and TPC/BSGF scores. For instance, the metric scores are expected to increase when a project adopts T24 as its standard, has more staff in its construction contractor, expends higher cost for its delivery, and was reported as more complex.

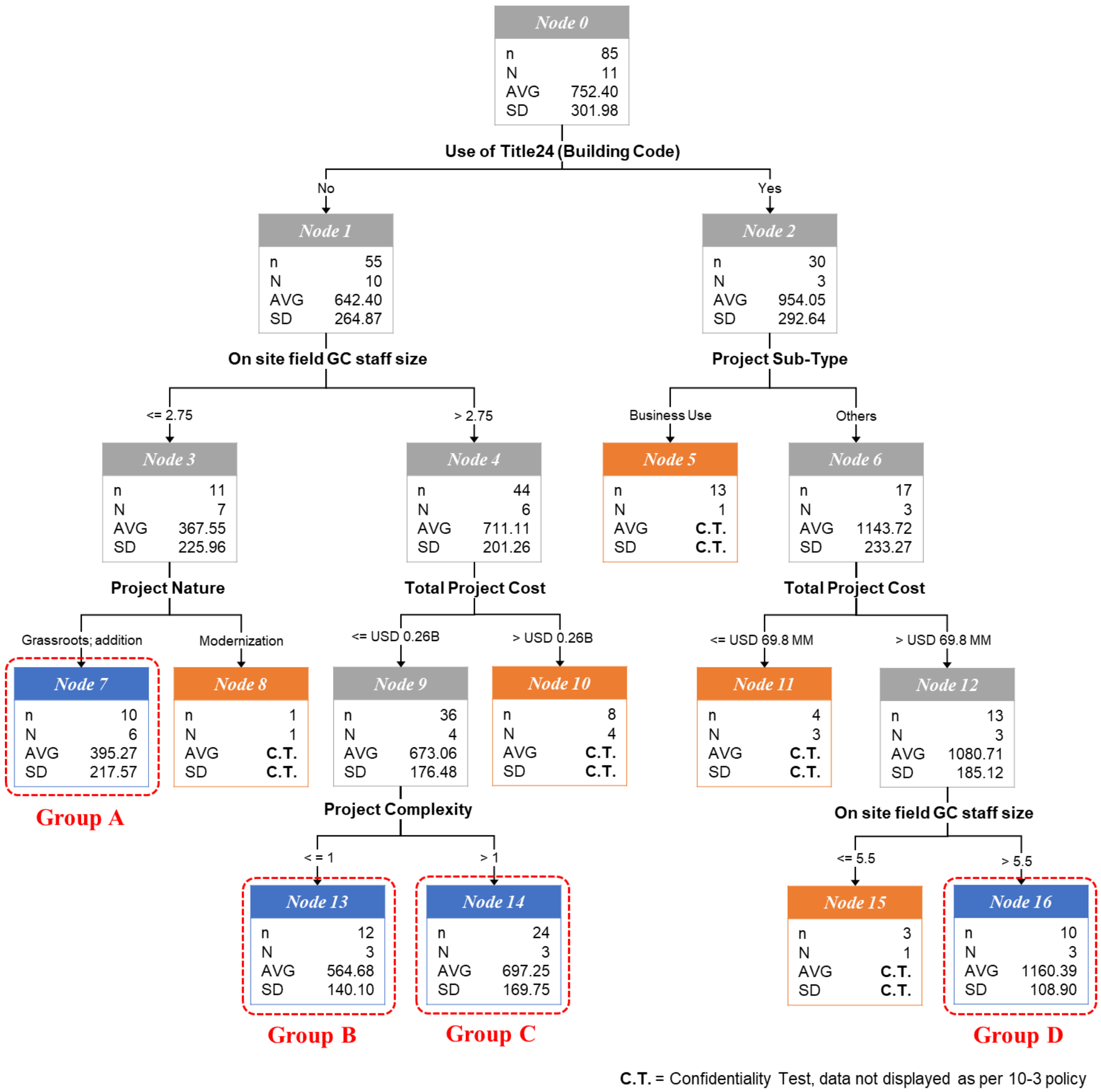


Figure 27: RT for project grouping – TPC/BGSF

The project grouping rules for TPC/BGSF based on the constructed tree are summarized in Table 11, and each line in the table represents a rule. There is a total of nine rules covering all four levels, which were extracted from the tree by following the threads. The percentage of project counts corresponding to each rule are provided, together with node number and reference node that indicates the node where contains similar projects to make performance comparison while satisfying the 10-3 policy. As an example of the practical interpretation of a given rule, group C (i.e., node 14) contains 28.2% of projects (24 out 85) which are similar in terms of four features that are closely associated with TPC/BGSF, i.e., T24, GC, TPC, and PC. The node reveals that if Title 24 is adopted as one of the building codes, the staff size of general contractor in FTE is greater than 2.75, TPC is larger than USD 0.26 billion, and the degree of complexity is 1 (i.e., lowest difficulty); the average TPC/BGSF scores of projects can be distinctively separated from those in other nodes. Accordingly, a comparative analysis of TPC/BGSF can be implemented using the set of projects in group A. However, in case of node 15, because all projects in the node were submitted by a single organization, the project is compared to all projects in the parent node (node 12). Accordingly, the benchmarking is made using the records in node 12, which includes 13 projects submitted from 3 organizations.

Table 11: Project grouping rules for TPC/BGSF

No.	**NN**	**RN**	**Rules**	**# PJT**	**% of PJT**
1	5	2	T24 [Yes]	13	15.3%
2	7	7	T24 [No]; GC <= 2.75; ST [Grassroots; Addition]	10	11.8%
3	8	3	T24 [No]; GC <= 2.75	1	1.2%
4	10	4	T24 [No]; GC > 2.75	8	9.4%
5	11	6	T24 [No]; ST [Others]	4	4.7%
6	13	13	T24 [No]; GC > 2.75; TPC <= 0.26B; PC = 1	12	14.1%
7	14	14	T24 [No]; GC > 2.75; TPC <= 0.26B; PC > 1	24	28.2%
8	15	12	T24 [Yes]; ST [Others]; TPC > 69.8M; GC <= 5.5	3	3.5%
9	16	16	T24 [Yes]; ST [Others]; TPC > 69.8M; GC > 5.5	10	11.8%

Note. NN = Node number; RN = Reference node number; and T24, GC, ST, PN, TPC, and PC represent the use of Title 24, the staff size of onsite field GC (in FTE), sub-type, project nature, total project cost, and project complexity, respectively.

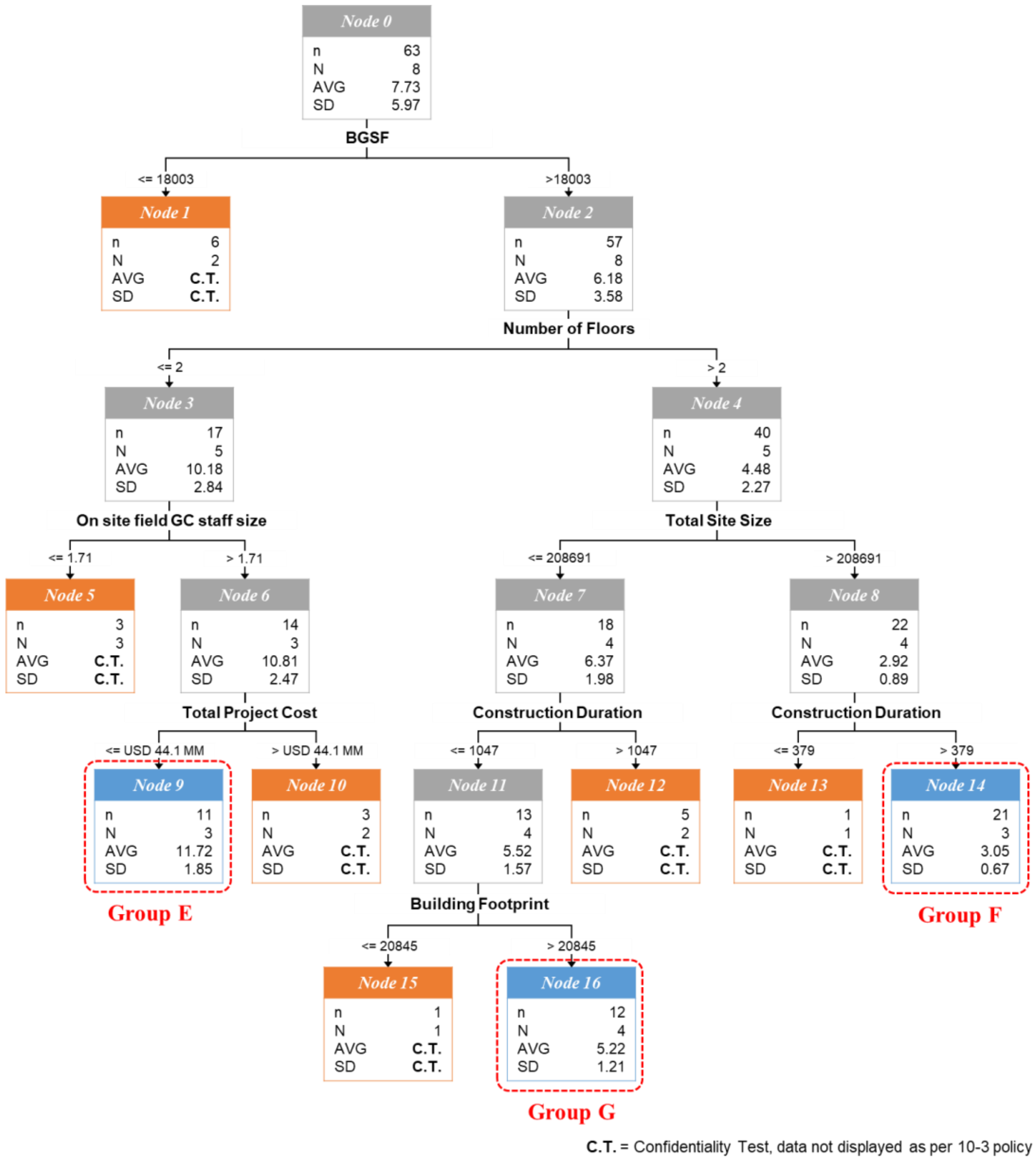


Figure 28: RT for project grouping – CPD/BGSF

A decision tree for CPD/BGSF was built using the CART algorithm and is presented in Figure 28. In the tree, BGSF and the number of building floors (NF) are used as the first and second level features, respectively; the third level features are GC and total site size (SS) in the unit of square foot; the fourth level features are TPC and construction duration (CD); and building footprint area (BF) are used as the last level feature. The CD is defined as the duration in the unit of days between the start date of construction based on notice to proceed (mobilization or commencement of foundation or driving piles) and the stop date of construction based on beneficial occupancy date (CII 2014). The SS is defined as the area of total site inside the project limit line (CII 2014). The leaf node in the figure was color-coded in the same manner as the tree constructed for TPC/BGSF; projects in leaf nodes 1, 5, 10, 12, 13, and 15 need to be merged with the closest node to satisfy the 10-3 policy while other leaf nodes (i.e., groups E to G) are groups of projects to be compared at each node.

Table 12: Project grouping rules for CPD/BGSF

No.	**NN**	**RN**	**Rules**	**# PJT**	**% of PJT**
1	1	0	All projects	6	9.5%
2	5	3	BGSF > 18003; NF <= 2	3	4.8%
3	9	9	BGSF > 18003; NF <= 2; GC > 1.71; TPC <= 44.1MM	11	17.5%
4	10	6	BGSF > 18003; NF <= 2; GC > 1.71	3	4.8%
5	12	7	BGSF > 18003; NF > 2; SS <= 208691	5	7.9%
6	13	8	BGSF > 18003; NF > 2; SS > 208691	1	1.6%
7	14	14	BGSF > 18003; NF > 2; SS > 208691; CD > 379	21	33.3%
8	15	11	BGSF > 18003; NF > 2; SS <= 208691; CD <= 1047; BF <= 20845	1	1.6%
9	16	16	BGSF > 18003; NF > 2; SS <= 208691; CD <= 1047; BF > 20845	12	19.0%

Note. NN = Node number; RN = Reference node number; and NF, GC, SS, TPC, CD, and BF represent the number of floors, the staff size of onsite field GC (in FTE), site size (in square foot), total project cost, construction duration (in days), building footprint (in square foot), respectively.

The grouping rules for CPD/BGSF are listed in Table 12 with each line indicating one of the nine rules identified. The rules described in Table 12 can be interpreted in a similar way to those of Table 11, based on rule descriptions, the percentage of project counts corresponding to each rule, and node number and reference node. For instance, if BGSF is larger than 18,003, the number of building stories is not greater than two, the staff size of general contractor in FTE is greater than 1.71, and the TPC is smaller than USD 44.1 million, the average CPD/BGSF scores (11.72) of corresponding projects (17.5% out of 63 projects) can be differentiated from those of other projects (6.88). This is also valid for projects included in groups F and G (i.e., nodes 14 and 16) that respectively account for 33.3% and 19.0%. However, in case of other nodes, i.e., 1, 5, 10, 12, 13, and 15, groups of similar projects need to be determined in their parent nodes due to limited records or organizations having submitted them.

4.4.2 Validation

4.4.2.1. *Comparison of grouped projects*

The decision trees generated distinct groups of similar projects suited for comparison of the two metrics, indicating that the trends of metric values derived from projects in each group may be different from one another. We employed ANOVA and post hoc test to assess whether the difference in the average metric score was significant across these groups. The homogeneity of variance for the samples used in two ANOVA tests was confirmed by Levene's test (Park et al. 2016).

Table 13: Summary of ANOVA analysis

Metric	Measure	Sum of Squares	df	Mean Square	F	Sig.
TPC/BGSF	Between Groups	2748956.00	3	916318.67	33.76	.000
	Within Groups	1411357.47	52	27141.49		
	Total	4160313.46	55			
CPD/BGSF	Between Groups	548.65	2	274.32	190.03	.000
	Within Groups	59.19	41	1.44		
	Total	607.84	43			

The results of ANOVA showed that differences among TPC/BGSF scores of groups A to D are significant with *p* value below 0.05, and so is among CPD/BGSF scores of groups E to G. The result shown in Table 13 implies that there were significant differences among the metric scores across the groups for both studied metrics. As presented in Table 14, multiple comparisons using the post hoc test (Tukey' HSD) indicated that the mean difference of each two groups were significant, with *p* value less than 0.05, except for the case between groups 1 and 2 ($p = 0.089$) indicating statistically significant differences across the groups.

Table 14: Results of post-hoc analysis (Tukey's HSD)

Metric	**Group (I)**	**Group (J)**	**Mean Diff (I-J)**	**Std. Error**	***p*-value**	**95% Confidence Interval**	
						Lower	**Upper**
TPC/BGSF	A	B	-169.405	70.540	0.089	-356.626	17.816
		C	-331.980	62.008	0.000	-496.556	-167.403
		D	-765.121	73.677	0.000	-960.667	-569.575
	B	A	169.405	70.540	0.089	-17.816	356.626
		C	-162.575	58.247	0.036	-317.168	-7.982
		D	-595.716	70.540	0.000	-782.937	-408.495
	C	A	331.980	62.008	0.000	167.403	496.556
		B	162.575	58.247	0.036	7.982	317.168
		D	-433.141	62.008	0.000	-597.718	-268.565
	D	A	765.121	73.677	0.000	569.575	960.667
		B	595.716	70.540	0.000	408.495	782.937
		C	433.141	62.008	0.000	268.565	597.718
CPD/BGSF	E	F	8.673	0.447	0.000	7.585	9.760
		G	6.498	0.502	0.000	5.278	7.717
	F	E	-8.673	0.447	0.000	-9.760	-7.585
		G	-2.175	0.435	0.000	-3.232	-1.118
	G	E	-6.498	0.502	0.000	-7.717	-5.278
		F	2.175	0.435	0.000	1.118	3.232

4.4.2.2. *Comparison of project grouping results derived from current and proposed methods*

The current method for healthcare project grouping uses four fixed features that identically apply across all NHFBP metrics. Table 8 presents the results generated on the basis of the current algorithms and shows how those features are utilized to group all of 89 projects for comparing each TPC/BGSF and CPD/BGSF. For TPC/BGSF, 11.8% of projects were grouped using all four features. However, in case of CPD/BGSF, there were no projects grouped using all the features due to the 10-3 policy, and thus *cost category* was ignored in order to expand a pool of similar projects using three features only. In other groups, three, two, or one feature was considered according to the algorithm displayed in Figure 25. For TPC/BGSF, 54.1% of projects were grouped using *project type*, *sub-type*, and *project nature*, and 18.8% of projects were grouped using two features only, i.e., *project type* and *sub-type*. The remaining projects (15.3%) were grouped by considering *project type* only. For CPD/BGSF, approximately 70% of projects were grouped as similar projects using three features. The remaining projects were grouped based on two or one features, as shown in Table 15.

The number of features utilized to generate sets of similar projects is illustrated in Figure 5 to compare the number of features for benchmarking TPC/BGSF and CPD/BGSF scores, based on current and proposed approaches. As shown in Figure 29, for TPC/BGSF, the proportion of project grouped using more than three features are almost similar between two methods; however, the new approach tends to use four features while three features are mostly used for the existing algorithm. Clearly, the RT-based approach tends to consider more features compared to the current method for both metrics.

Table 15: Project grouping results derived from the current method

	Features				Descriptive				
	PT	PS	PF	CC	% cases	Mean	SD	Min	Max
TPC/BGSF									
1	MOB	BU	GR	15~50	11.8%	580.6	199.9	189.0	936.8
2	INP	TE	GR	-	15.3%	780.1	317.3	266.7	1318.1
3	MOB	BU	GR	-	22.4%	645.0	163.1	265.1	949.5
4	MOB	IU	GR	-	16.5%	793.1	330.9	472.4	1555.3
5	INP	TE	-	-	11.8%	1006.4	320.4	513.4	1545.0
6	MOB	BU	-	-	4.7%	736.3	435.0	90.3	1038.5
7	MOB	IU	-	-	2.4%	778.6	76.7	724.3	832.8
8	INP	-	-	-	15.3%	793.0	358.4	102.7	1244.1
CPD/BGSF									
1	INP	TE	GR	-	37.5%	4.54	3.74	1.69	13.72
2	MOB	BU	GR	-	15.6%	8.18	4.75	2.84	23.75
3	MOB	IU	GR	-	15.6%	9.65	7.83	2.45	25.29
4	INP	TE	-	-	7.8%	3.23	1.91	0.23	5.64
5	MOB	BU	-	-	3.1%	15.28	9.14	2.17	25.00
6	MOB	IU	-	-	9.4%	7.39	3.27	5.07	9.70
7	INP	-	-	-	9.4%	6.37	4.27	2.84	13.47

Note. BU, IU, TE, and GR stand for business use, institutional use, tertiary, and grassroots, respectively.

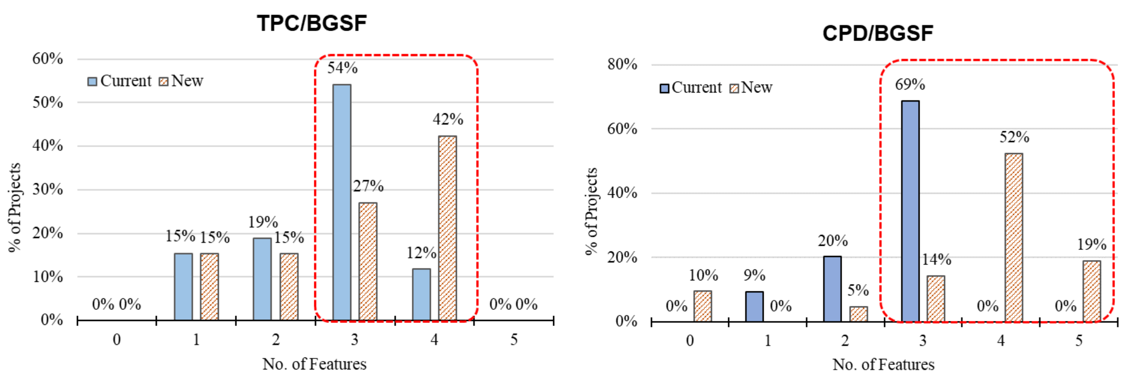


Figure 29: Comparison between current and proposed methods – number of features

Moreover, the difference between estimated errors based on the results of project grouping derived from the existing and proposed methods are evaluated using MEA and RMSE. As shown in Table 16, the tree-based approach proposed in this study generated a set of similar projects having a better absolute fit of model to the data than that generated using the existing approach. This result indicates that the RT-based method generated a better grouping than the existing method with regard to metric.

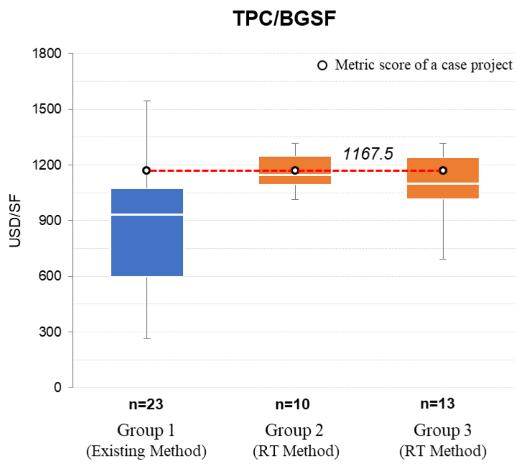
Table 16: Comparison of errors between existing and proposed grouping methods

	TPC/BGSF		**CPD/BGSF**	
Measures	Existing	Tree-based	Existing	Tree-based
Mean absolute error	216.82	130.93	3.74	1.02
Root mean squared error	279.97	169.32	5.12	1.44

In addition to the effectiveness of the proposed project grouping method, it was found that there are certain advantages of the proposed method over the existing one to note. It was found that the proposed method utilizes the flexible sets of project attributes that better explain the variation of target metric than that of the existing one (i.e., *project type*, *sub-type*, *project nature*, and *cost category*). For instance, the new method found six and seven unique attributes closely associated with TPC/BGSF and CPD/BGSF, respectively, and most of the attributes employed in the existing method were not identified as meaningful ones in the proposed approach. If different metrics are considered for project grouping using the new method, the similarity of projects will be captured using different sets of attributes and project grouping rules. Moreover, the new approach can provide organizations with meaningful insights into critical features related to a certain performance. For instance, compliance with the building energy efficiency standards [Title 24 from CEC (2019)] was identified as the most influential feature that increases the amount of project cost per building gross area, which is never considered when the existing grouping method was used. It is widely accepted that the initial costs of energy efficient facilities are much higher than conventional projects, although longer-term cost savings in operations and maintenance recover those costs (Olubunmi et al. 2016; Robichaud and Anantatmula 2011; Zuo and Zhao 2014). This attribute was captured through the proposed method, which provides anecdotal evidence that the method captures meaningful features. More importantly, the proposed method allows for more targeted performance comparisons by capturing similarity in a systematical approach, which reduces the search space of determining a group of similar projects.

4.5. DISCUSSION

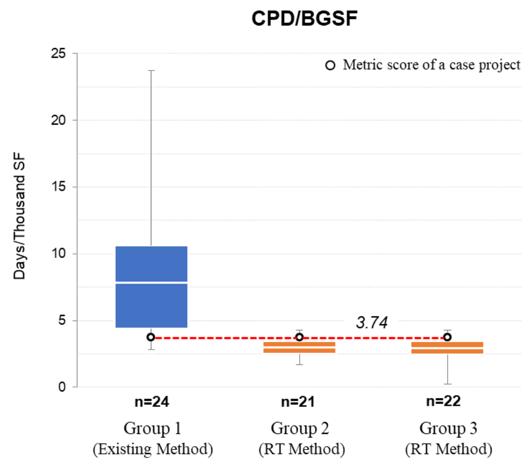
Given the different characteristics of healthcare projects, a robust project similarity methodology to support project performance comparison is a crucial component for generating reliable benchmarking. Figure 30 presents the box and whisker plots generated based on the sets of projects similar to each of two case projects for benchmarking TPC/BGSF and CPD/BGSF scores. It should be noted that one advantage of decision trees is their flexibility in group extraction in a hierarchical tree-like structure (Mistikoglu et al. 2015). For each metric, a distinct group of similar projects was determined at a leaf node as discussed in the previous section, but it can be adjusted in such case that performance comparison needs to be made using a larger number of projects. This adjustment can be made by successively selecting groups up in the parent nodes of a given node, depending on the strategy of how we group projects. In this regard, three box and whisker plots were created per metric: one for metric scores of projects similar to a case determined by using the existing method (Group 1), two plots for those determined at a leaf node (Group 2) and at the parent node of the leaf (Group 3), using the RT-based method. The project features of projects included in each group were also provided along with the information of what specific features were considered for determining the similar projects of a case project by group. Note that in the figure, used features for generating each group were represented in texts in bold Italic, whereas unused ones were grayed out.



Used features for each case (TPC/BGSF)

Feature	Group 1	Group 2	Group 3
PT	***INP***	INP	INP;MOB
PS	***TER***	***SEC;TER***	***SEC;TER;INS***
T24	Yes;No	***Yes***	***Yes***
TPC	266-1545MM	***> 69.8MM***	***> 69.8MM***
GC	0-56	***> 5.5***	0-56

Note. INP= Inpatient hospital, MOB= Medical office building, TER= Tertiary, SEC= Secondary, INS= Institutional use, and a set of features considered for the determination of similar projects with a case is indicated in bold italic.



Used features for each case (CPD/BGSF)

Feature	Group 1	Group 2	Group 3
PT	***MOB***	INP;MOB	INP;MOB
ST	***INS***	SEC;TER;INS;BUS	SEC;TER;INS;BUS
PN	***GR***	GR;BR;AD	GR;BR;AD
BGSF	9011-276685	***> 18003***	***> 18003***
NF	1-9	***> 2***	***> 2***
SS	39204-2178000	***> 208691***	***> 208691***
CD	183-1199	***> 379***	82-1628

Note. INP= Inpatient hospital, MOB= Medical office building, TER= Tertiary, SEC= Secondary, INS= Institutional use, BUS= Business use, GR= Grassroots, BR= Brownfields, AD= Addition, and a set of features considered for the determination of similar projects with a case is indicated in bold italic.

Figure 30: Benchmarking results of TPC/BGSF and CPD/BGSF for a case project

As shown in the figure, relative performance positions of a project against similar projects determined by two algorithms are remarkably different for both metrics. Based on the result derived from the existing algorithm (Group 1), the project seemed to spend more money per BGSF compared to its peers, given that its score is located above the third quartile; however, the position of the score is close to median when comparison projects were chosen using the proposed approach in this study (Group 2). The same is valid for the case of CPD/BGSF: the current and proposed approaches lead to opposite conclusions. When the score was compared against a group of projects selected by the current method, the project appears to have spent less time to finish construction work per BGSF; however, the performance is conversely interpreted when similar projects were selected by the proposed approach. Those different benchmarking outcomes imply that the results of project grouping derived from the new method can offer an alternative and complementary perspective to those derived from the existing method. Group 3 for TPC/BGSF contains a set of similar projects determined at a parent node of leaf node by disregarding a feature of GC, which enabled three additional projects to be included in the group of similar projects. As projects with low scores of TPC/BGSF were incorporated into the group, the score of the case project was located in the middle of the second and third quartiles. The group 3 for CPD/BGSF was defined by adding a single project to group 2 by neglecting a feature of CD that generated two leaves. Although a couple of cases were investigated, it was found that groups of similar projects could be selected in a flexible manner by using parent nodes if necessary.

One of the well-known limitations of a single tree model is that the result tends to be highly unstable in prediction (Loh 2011; Pham 2006; Ville 2006). A single decision tree is known to have high variance, resulting in unstable classification/prediction because an alternative subsample of training data can significantly change the leaf nodes (Loh 2011).

This issue can be overcome by bootstrap aggregating (bagging) or leveraging other techniques considered quite powerful and effective tree-based models, e.g., random forests and gradient boosting machines (Pham 2006). However, given that a prerequisite for project grouping in benchmarking is to allow meaningful comparisons for a given project, a single tree approach was adopted for this study. Considering the limitation of the single tree model, it is recommended that the rules should be modified on a regular or batch basis (e.g., time basis or number of projects basis) as data accumulates.

In addition, it is recommended that future research addressing the knowledge of domain experts' opinions is required prior to applying this approach to real benchmarking practice. Due to the scope of this study, this chapter lacks a detailed discussion of features identified as important when trees were built. The relationship between selected features and metric scores needs to be validated in more detail, and the knowledge of domain experts can be incorporated in the feature selection step.

4.6. CONCLUSION

Based on identified limitations of the existing method to capture similarity of healthcare projects, a new approach was proposed to group the projects using a decision tree algorithm. The sets of similar projects grouped using the new approach showed that different performance metrics can be benchmarked within distinct groups determined based on meaningful features that are more closely related to the metric. According to ANOVA and post hoc tests, there is a statistically significant ($p < 0.05$) or near significant ($p < 0.1$) difference in the average of their metric scores across most groups. The superiority of the new approach over the existing grouping method was validated by comparing the number and quality of features used to generate groups of similar projects and the amount of errors in metric values. The proposed method allows for more targeted performance comparisons by capturing similarity using flexible sets of meaningful features, which reduces the search space of determining a group of similar projects. It also can generate the sets of similar projects flexibly, which is suited for comparing each of the selected metrics, ultimately being applicable to all metrics adopted in NHFBP. The result is expected to help organizations gain better insights into their relative performance position when benchmarking their capital projects.

Chapter 5 Conclusions and Future Research

This chapter synthesizes the findings of this dissertation per research question. It describes the intellectual contributions and provides a discussion on the limitations of this research, along with potential future studies.

5.1. CONCLUSION AND CONTRIBUTIONS

Focusing on healthcare projects, the goal of this dissertation was to improve current benchmarking processes by leveraging Building Information Modeling (BIM) for data collection and by capturing project similarity for credible performance comparisons. This research opens an important discussion in the benchmarking domain regarding the transition toward automated implementations. The results of this research lay a groundwork of an automated benchmarking approach that leverages emerging information technologies, enabling a large-scale project data to be captured and processed in an efficient manner and providing the benchmarking users with better insights into benchmarking outcomes.

From the users' perspective, the BIM-based benchmarking can enable them to implement benchmarking with reduced time and manual input because data collection and entry can be vastly reduced when BIM models are used as a benchmarking data repository. It is expected that this automated (or semi-automated) benchmarking approach can lead to wide-scale adoption of benchmarking practice in the industry by streamlining the current manual benchmarking practice. Moreover, this dissertation proposes a new project grouping method that allows for more targeted performance comparisons by capturing similarity using flexible sets of meaningful features. The new approach can help organizations gain better insights into their relative performance position when benchmarking their capital projects.

This research was conducted in response to the research questions described in Chapter 1. Major findings by research question are presented as follows:

What is the potential of BIM models to feasibly support data needed for NHFBP, and what are the essential functions of the BIM-based benchmarking tool to streamline the benchmarking process?

Chapter 2 addressed the feasibility study for the BIM-based benchmarking approach and its functional requirements of such an approach. Based on a comprehensive list of performance metrics tailored for healthcare facilities, the chapter first investigated the potential of BIM to feasibly support data needed for the metric through close scrutiny of contents embedded in real-world models collected from six healthcare projects. The result of this study showed that BIM, although supplemental data are required, can provide a considerable amount of data to measure NHFBP metrics (i.e., 82.8% of metrics are partially or completely measurable), so have high potential to replace current manual data collection and entry by users. As the next step, this study, then, established a vision for a BIM-based benchmarking system by proposing functional requirements for such a tool. Functional requirements were represented using (1) a set of use cases that describe software requirements, and (2) and data flow diagrams (DFD) that model the functions of the envisioned BIM-based benchmarking approach. A demonstration was conducted using publicly available healthcare facility models with minor modifications to support sufficient data for measuring certain metrics.

Although many research efforts have been made to automate diverse manual processes in the AEC industry, this study is one of the first studies which attempt to integrate BIM with project performance benchmarking practices. Thus, this research contributed to bridging the gap by conducting a feasibility study and establishing functional requirements which corroborate a smooth introduction of BIM to an existing benchmarking program (i.e., NHFBP). The findings of this study will provide a stepping-stone for accomplishing a BIM-based benchmarking tool for wide-scale benchmarking implementation in the AEC industry.

How can the data acquisition process from BIM models be formalized in order to obtain usable benchmarking data needed for NHFBP?

Chapter 2 found that BIM has great potential to feasibly support project data needed for a healthcare benchmarking program, which is a great opportunity to streamline the current practice. However, it is still unclear how to obtain useful and reliable benchmarking data from BIM models. This issue was addressed in Chapter 3 by developing a formalized schema that can be used to obtain reliable benchmarking data using information stored in BIM models. Specifically, the schema identifies specific transformation processes applicable to different sets of benchmarking data required for NHFBP, focusing on IFC and COBie so as to establish a consistent approach to process BIM data without the barriers of interoperability issues. The schema also defines specific sets of transformations applicable to different groups of benchmarking data classified based on their attributes using a total of 14 distinctive procedures (8 for IFC and 6 for COBie) represented by a functional library. For the validation, we collected performance data from two healthcare projects that donated two IFC models for this research, enabling a comparative analysis using data acquired from two sources. Through the validation, it was found that the schema generated relatively accurate performance data included bed, space, and medical equipment categories, while there was a large discrepancy in data concerned with building system and building exterior categories. The observed deviance in the data values was explained by the inaccurate representation of data or missing data in the studied model as well as the possibility of typing errors in the manually submitted data. It is expected that the accuracy of data will increase if models provide an accurate representation of the actual building. Furthermore, the research method presented in this research is expected to be applied to different benchmarking programs geared toward other industry sectors (i.e., commercial and residential buildings, or industrial projects). The method can be implemented to develop a sector-specific BIM-based benchmarking system, followed by establishing new performance metrics suitable to a particular industry sector.

How to capture similarity for healthcare projects for credible performance comparisons?

Given the different characteristics of healthcare projects, a robust project grouping methodology to support project performance comparison is a crucial component for generating reliable benchmarking. A new project grouping approach was proposed in Chapter 4 in order to group the projects using a decision tree algorithm. The sets of similar projects grouped using the new project grouping approach showed that different performance metrics can be benchmarked within distinct groups determined based on meaningful features that are more closely related to the metric. According to ANOVA and post hoc tests, there is a statistically significant ($p < 0.05$) or near significant ($p < 0.1$) difference in the average of their metric scores across most groups.

The advantage of the new approach over the existing grouping method was validated by comparing the number of features used to generate groups of similar projects and the number of errors in metric values. The proposed method allows for more targeted performance comparisons by capturing similarity using flexible sets of meaningful features, which reduces the search space of determining a group of similar projects. It also can generate the sets of similar projects flexibly, which is suited for comparing each of the selected metrics, ultimately being applicable to all metrics adopted in NHFBP.

In summary, the intellectual contributions of this research include:

- This dissertation introduced a novel benchmarking approach that can leverage data stored in BIM models and developed a research methodology to conduct the feasibility of a BIM-based approach and to define the functional requirements of such an approach.
- This dissertation proposed a formalized representation schema to establish a consistent approach to process BIM data for reliable and usable benchmarking data acquisition. The schema allows for the inclusion of new metrics.
- This dissertation developed a systematic methodology that allows for more targeted performance comparison using a set of critical and flexible features that are closely associated with performance metrics. The benchmarking result generated using the new approach allows for more targeted performance comparison and to support decision making for performance improvements.
- The research methods presented in the dissertation can be implemented to advance different benchmarking programs tailored for other industry sectors.

5.2. LIMITATIONS AND FUTURE RESEARCH

Major limitations associated with the envisioned BIM-based benchmarking approach and project grouping methods are worthy of discussion. This section describes the issues identified throughout this dissertation and several directions for future research.

5.2.1 Toward a fully automated BIM-based benchmarking

First, one of the issues related to BIM production and its contents is that each project followed different naming conventions for naming elements. Existing BIM standards noted that naming conventions for all elements in BIM should be succinct, useful, and descriptive in order to allow for easy identification and be easily understood, which facilitates data extraction from BIM. As an effort to overcome the issue, the OmniClass Construction Classification System (known as OmniClassTM or OCCS) describes how things are called and how those names are arranged and structured, which can be used for organizing and retrieving information for the construction industry. For instance, OmniClass tables 13 (space by function) and 23 (products) provide the definitions and taxonomies of spaces and manufactured items with their unique identification numbers. Although more systematic data extraction could be possible when this information can be attached to BIM objects, it was found that the classification system was not used in the collected models. In response, several researchers proposed approaches to overcome the barrier concerning different naming conventions for the same elements such as a name-based mapping and ontology-based mapping as discussed in Chapter 3. However, this issue was beyond the scope of this dissertation, and mapping between BIM and NHFBP data manually performed. A systematic or automated approach that links NHFBP data with specific BIM data is considered as future research.

Second, this research leveraged BIM as a single data repository that supports NHFBP data. In Chapter 2, BIM, although supplemental data are required, can provide a considerable amount of benchmarking data, so have high potential to replace current manual data collection and entry. However, given that BIM typically does not embed all necessary information required for NHFBP, the data collection and entry is not fully automated. To overcome this problem, supplementary databases can be linked with BIM, which enables all necessary data to be obtainable. For example, if external cost and schedule databases are connected with BIM models, and cost and schedule data could be systematically extracted and used for measuring a variety of metrics that are currently not measurable when BIM is used as a single data source. As a path forward, an approach to integrating BIM with diverse external databases will be investigated.

Third, the data extracted from the model should provide an accurate representation of the actual products, considering the fact that the reliability of benchmarking outcomes largely depends on the degree of accuracy in information embedded in models, as identified from the cases of data related to building system and envelope categories (Chapter 3). The data-intensive and properly built models are, thus, required to fully exploit the benefits of the BIM-based benchmarking. However, manually updating the model and detailed properties embedded in it is cumbersome and extremely time-consuming, which poses a challenge of keeping BIM information up-to-date (Leite 2020). In this regard, modelers need to manage and develop BIM products with the appropriate Level of Detail (LoD) prior to using them for benchmarking.

Fourth, it is anticipated that the BIM-based benchmarking can be implemented using the models produced in any phase, which would enable project stakeholders to proactively assess their project performance throughout the entire project delivery process. This procedure can be conducted at any phase of the model to improve building design for better building performance and guide the decision-making process in the early or later design phase to maximize the benefits. It also helps in evaluating design options and solutions in real time when BIM models are available. However, this benchmarking approach necessitates updating the use cases and data flow proposed in Chapter 2, given the fact that a sequence of interaction between a system and an external actor needs to be modified, along with changes in the data flow process of the system, which warrants additional future research.

Fifth, regarding the established schema for the BIM-based benchmarking, validating the accuracy of data produced using the proposed schema is challenging as models reflecting as-built facilities are not available. If the objects designed in the virtual environment provides an accurate representation of the actual building (e.g., as-built models), the accuracy of data is expected to increase. Moreover, the data representation schema proposed in this research focuses on the existing BIM specification and standard (i.e., IFC and COBie) that are regularly updated, and this change may require the current representation to be modified in order to obtain benchmarking data from models.

Sixth, although the use of BIM is evolving in the construction industry, there is still a wealth of existing facilities constructed without BIM, and those projects are able to implement benchmarking by undergoing the existing manual process. However, in order to carry out benchmarking regardless of BIM usage, manually submitted data need to be merged with those extracted from BIM models and be stored in a single data frame. The merging process can be explored focusing on how to store data obtained from BIM models to be matched with the existing NHFBP database and how to populate those data in the database. Therefore, merging two data frames considered another future direction.

Seventh, the BIM-based benchmarking approach presented in Chapters 2 and 3 do not address one of the major problems identified from the current NHFBP practice, i.e., manual data validation. Although the reliability of data extracted from BIM models can decrease the burden for validation, it still needs to be manually implemented. The BIM-based benchmarking should be driven forward to address entire issues of the current benchmarking practice.

Eighth, the proposed BIM-based benchmarking system would be improved by gauging the usefulness and feasibility of the system for healthcare facilities once the actual tool is developed. I recognize the importance of incorporating various NHFBP user perspectives in the functional requirements and the representation schema established in this dissertation; hence, follow-up data collection to aimed at evaluating the tool will be conducted in a future study.

Last but not least, this dissertation developed a BIM-based benchmarking approach focusing on healthcare facility projects. Future work can expand to include additional industry sectors following the same methodology. The research approach described in this report can be implemented to develop a sector-specific model-based benchmarking system, followed by establishing new performance metrics suitable to a particular industry sector.

5.2.2 Toward a more reasonable project grouping

First, the proposed project grouping method was established by analyzing a small sample of healthcare projects (i.e., a total of 89 datasets). However, some drawbacks can emerge in case that a large number of projects are grouped because of the characteristics of a model utilized to generate a set of groups in this study. If a much larger sample of projects is grouped, the tree can grow until an end node reached at the bottom of the tree by reducing errors and capturing a large number of features, ultimately leading to the narrow distributions of metric scores of similar projects. The grouping results, in this case, are likely to decrease confidence in the final benchmarking outcomes. This problem can be addressed by modifying tree pruning methods in two ways; first, the number of features that subdivide nodes would be adjusted in order to limit the size of trees. For instance, the tree can be designed to grow until a certain number of levels (i.e., the number of partitioning data). The minimum number of projects within a leaf node also can be adjusted so that the tree stops growing if the node contains less than a certain number of projects. However, specific thresholds limiting the tree size need to be confirmed through intensive experimental tests using collected project data. Considering this issue, it is recommended that the grouping process should be modified as data accumulates.

Second, another limitation of the proposed project groping method is that it generates groups of projects considering all of the available input variables collected from NHFBP as candidate features. This approach can help project stakeholders identify what features are meaningful for enhancing metric scores of interests. However, as discussed in Chapter 4, project types, nature, and cost have been widely used as critical attributes for project grouping in various benchmarking programs, which indicates that those attributes can be more important predictors representing project characteristics than the others. For instance, the regression tree determined the use of Title-24 as a primary feature that partitions the entire projects into two child nodes. However, benchmarking users could gain better insights into the grouping results when certain features representing project types are used as primary features. The rationale behind this idea is that healthcare facilities consist of different types (e.g., in-patient hospital, medical office building, and central utility plant) delivered through one of multiple project natures (e.g., grassroots, brownfield, and renovation) with various range of cost and schedule, which could be crucial components for capturing project similarity rather than a specific building code (e.g., Title-24). In this regard, certain features can be applied for project grouping by default prior to running the regression tree model proposed in this dissertation. This approach would provide an opportunity to develop more reliable project groups, ultimately leading to more reasonable and intuitive metric comparisons. However, it raises another issue of how similar types of projects should be defined and what features should be applied by default, which requires intensive experimental tests using a large number of datasets. This issue, thus, needs further clarification. It is also recommended that future research incorporates the knowledge of domain experts' opinions and knowledge to prioritize influential project attributes.

Third, one of the well-known limitations of a single tree model is that the result tends to be highly overfitting. A single decision tree is known to have high variance, resulting in unstable classification/prediction because an alternative subsample of training data can significantly change the leaf nodes (Loh 2011). This issue can be overcome by bootstrap aggregating (bagging) or leveraging other techniques considered quite powerful and effective tree-based models, e.g., random forests and gradient boosting machines (Pham 2006). However, given that a prerequisite for project grouping in benchmarking is to allow meaningful comparisons for a given project, a single tree approach was adopted for this study. Considering the limitation of the single tree model, it is recommended that the rules should be modified on a regular or batch basis (e.g., time basis or number of projects basis) as data accumulates. In addition, this study was implemented using a small sample of projects (89 projects) that made it challenging to apply a wide range of techniques to solve the current problem. Therefore, as a future direction, other algorithms or modeling methods (e.g., K-nearest neighbors, and data envelopment analysis) may need to be applied for better project grouping with a larger set of projects.

Lastly, it is recommended that future research eliciting and incorporating the knowledge of domain experts' opinions is required prior to applying the new project grouping approach to real benchmarking practice. The effectiveness of the proposed method was validated through quantitative evaluations, e.g., the numbers of features and estimated errors. A follow-up subjective assessment was implemented by providing anecdotal evidence that the method captured meaningful features. However, a further qualitative investigation will be required by incorporating domain experts' input to enhance the reliability of the proposed grouping method.

5.2.3 Toward BIM-based project grouping

The proposed project grouping process was initiated by investigating the entire benchmarking data collected through multiple types of variables stored in the NHFBP database in categorical or continuous data formats. Given the limited information stored in current BIM models, a possibility of coupling BIM and project grouping method was not explored in this dissertation, which warrants additional research, especially in addressing how BIM data can be leveraged to support the new project grouping method. BIM is increasingly being used by AEC organizations to improve project performance. It is evident that the centralized and integrated nature of the design information in BIM models can provide a very context rich platform for the capture, storage, and dissemination of the knowledge generated during the design and construction processes, which would offer a great opportunity of supporting information required for project grouping proposed in this dissertation. However, the proposed project grouping method relies on different types of project information submitted by project stakeholders based on objective and subjective assessment upon their projects. In this regard, a pilot study can be implemented by exploring what features should be used for the grouping and what features can be supported by BIM models, as a path forward. The outcomes of the study would help improve efficiency in project grouping tasks by capturing crucial features from the models.

Appendix 1: NHFBP Metric Definitions

Category	Definition
Cost	$ Actual Project Cost/BGSF
	$ Total Site Development Cost/Site Size
	$ Total Site Development Cost/BGSF
	$ Total Building Const. Cost/BGSF
	$ Non-Capitalized Costs/BGSF
	$ Non-Capitalized Costs/Total Building Const. Cost
	$ Total Building Commissioning Cost/Total Building Const. Cost
	$ Total Building Commissioning Cost/BGSF
	$ Commissioning - Agent Cost/Total Building Const. Cost
	$ Commissioning - Contractor's Cost/Total Building Const. Cost
	$ Commissioning - Owner Personnel Cost/Total Building Const. Cost
	$ Artwork and Plants /Total Building Const. Costs
	$ Furnishings /Total Building Const. Costs
	$ Roof Garden/sf. of Roof Garden
	$ Bridge/sf. of Bridge
	$ Mechanical Tunnel/sf. of Mechanical Tunnel
	$ Pedestrian Tunnel/sf. of Pedestrian Tunnel
	$ Connecting Concourse/sf. of Connecting Concourse
	$ Imaging Equipment/$ Total Building Const.
	$ Imaging Equipment/Population
	$ Imaging Equipment/sf. of Imaging Department
	$ Reused Medical Equipment/$ Capital Medical Equipment
	$ Capital Medical Equipment/BGSF
	$ Capital Medical Equipment/DGSF
	$ Capital Medical Equipment/Population
	$ Foundation/BGSF
	$ IT Cost/BGSF
	$ Actual Cost of CUP/Equivalent sf.
	$ CM Pre-Const. Fees/$ Total Building Const.
	$ Professional Fees/$ Total Building Const.
	$ Const. Contingency/$ Total Building Const.
	$ Const. Contingency/$ Cost of Work
	$ Contractor's General Condition/$ Total Building Const.

Category	Definition
Cost	$ Contractor's General Condition/$ Cost of Work
	$ Supervision/$ Total Building Const.
	$ Supervision/$ Cost of Work
	$ Supervision/BGSF
	$ Contractor's Fee/$ Total Building Const.
	$ Contractor's Fee/$ Cost of Work
	$ Contractor's Fee/BGSF
	$ Insurance/$ Total Building Const.
	$ Insurance/$ Cost of Work
	$ Local Taxes/$ Total Building Const.
	$ Local Taxes/$ Cost of Work
	$ Local Taxes/BGSF
	$ Project Management and Agent Fees/$ Total Building Const.
	$ Total Building Const. Cost/FTE for Owner, Staff, Architect, Consultant
	$ Total Building Const. Cost/FTE for GC CM
	$ Total Building Const. Cost/FTE for Owner PM
	$ Masterformat Division*/BGSF
	$ Masterformat Division*/Site Size
Schedule	Days/thousand BGSF, for Front End Planning/Programming
	Days/thousand BGSF, for SD (including RFP for Design-Build)
	Days/thousand BGSF, for Detail Design (DD/CD)
	Days/thousand BGSF, for Permitting
	Days/thousand BGSF, for Bidding
	Days/thousand BGSF, for Procurement
	Days/thousand BGSF, for Const.
	Days/thousand BGSF, for Activation/Move-In
	Planned Phase Duration/thousand BGSF, for Programming
	Planned Phase Duration/thousand BGSF, for Schematic Design
	Planned Phase Duration/thousand BGSF, for Detail Design (DD/CD)
	Planned Phase Duration/thousand BGSF, for Permitting
	Planned Phase Duration/thousand BGSF, for Bidding
	Planned Phase Duration/thousand BGSF, for Procurement
	Planned Phase Duration/thousand BGSF, for Const.
	Planned Phase Duration/thousand BGSF, for Activation/Move-In
	Actual Phase Duration/thousand BGSF, for Programming
	Actual Phase Duration/thousand BGSF, for Schematic Design

Category	Definition
Schedule	Actual Phase Duration/thousand BGSF, for Detail Design (DD/CD)
	Actual Phase Duration/thousand BGSF, for Permitting
	Actual Phase Duration/thousand BGSF, for Bidding
	Actual Phase Duration/thousand BGSF, for Procurement
	Actual Phase Duration/thousand BGSF, for Const.
	Planned Phase Duration/thousand BGSF, for Activation/Move-In
Dimension	DGSF/BGSF
	% Atrium Space OF BGSF
	sf. of Roof Gardens/BGSF
	Warm Shell sf./ BGSF
	Warm Shell sf./ DGSF
	Cold Shell sf./ BGSF
	Cold Shell sf./ DGSF
	Interstitial Space/Deck sf./ BGSF
	Enclosed Mechanical Penthouse sf./ BGSF
	sf. Exterior Skin Area/BGSF
	sf. of Glass/sf. Skin Area
	sf. of EIFS/sf. Skin Area
	sf. of Brick/sf. Skin Area
	sf. of GFRC/sf. Skin Area
	sf. of Plaster/sf. Skin Area
	sf. of Metal Panels (Al and steel)/sf. Skin Area
	sf. of Wood/sf. Skin Area
	sf. of Stone/sf. Skin Area
	(Total sf. of Parking structure - Office or Retail sf.)/# Parking stalls
	Total Structured Parking Stalls/ # of Stalls Below Grade Levels
	sf. of Retail Space or Office Space /Total sf. of structured Parking
Planning	Population (per thousand people)/# Total Licensed Beds
	BGSF/Population (per thousand people)
	Total Volume (c.f.)/BGSF
	BGSF/Building Footprint Area
	# Total Licensed Beds/# C.T.
	Population (per thousand people)/# C.T.
	# Total Licensed Beds/# MRI
	Population (per thousand people)/# MRI
	# Total Licensed Beds/# Angiography

Category	Definition
Planning	Population (per thousand people)/# Angiography
	# Total Licensed Beds/# Heart Cath
	Population (per thousand people)/# Heart Cath
	# Total Licensed Beds/# Mammography
	Population (per thousand people)/# Mammography
	# Total Licensed Beds/# Other Radiographic Equipment
	Population (per thousand people)/# Other Radiographic Equipment
	# Total Licensed Beds/# Ultrasound
	Population (per thousand people)/# Ultrasound
	# Total Licensed Beds/# Scintillation Gamma Cameras
	Population (per thousand people)/# Scintillation Gamma Cameras
	# Total Licensed Beds/# SPECT/CT
	Population (per thousand people)/# SPECT/CT
	# Total Licensed Beds/# PET
	Population (per thousand people)/# PET
	# Total Licensed Beds/# PET/CT
	Population (per thousand people) # PET/CT
	# Total Licensed Beds/# Linear Accelerators
	Population (per thousand people)/# Linear Accelerators
	# Total Licensed Beds/# Isotope Treatment Units
	Population (per thousand people)/# Isotope Treatment Units
	# Total Licensed Beds/# Other Imaging Equipment
	Population (per thousand people)/# other Imaging Equipment
	BGSF/# HVAC zone
	BGSF /Cooling Capacity (tons)
	BGSF /Heating Capacity (MBh)
	BGSF/Total Fan Supply (hp)
	BGSF/Boiler Capacity (hp)
	BGSF/Total Return/Exhaust Fan (hp)
	Total Building Supply (cfm)/BGSF
	Total Building Return/Exhaust (cfm)/BGSF
	Electrical Power Service Size (KW)/BGSF
	Total Lighting (KW)/BGSF
	Cogeneration Capacity (KW)/BGSF
	Total License Beds/# Private Single Bedrooms
	Population (per thousand people)/# Private single Bedrooms

Category	Definition
Planning	Total License Beds/# Semi - Private single Bedrooms
	Population (per thousand people)/# Semi - Private single Bedrooms
	Total License Beds/# Med and Surg Beds
	Population (per thousand people)/# Med and Surg Beds
	Total License Beds/# Critical Care Beds
	Population (per thousand people)/# Critical Care Beds
	Total License Beds/# of Telemetry Beds
	Population (per thousand people)/# of Telemetry Beds
	Total License Beds/# Behavioral Health Beds
	Population (per thousand people)/# Behavioral Health Beds
	Total License Beds/# Labor & Delivery Beds
	Population (per thousand people)/# Labor & Delivery Beds
	Total License Beds/# Basinets
	Population (per thousand people)/# NICU Basinets
	Total License Beds/# of Contingency Beds
	Population (per thousand people)/# of Contingency Beds
	BGSF/# of Contingency Beds
	BGSF/# Total License Beds
	Total License Beds/# OR's
	Population (per thousand people)/# OR's
	Total License Beds/# Procedure Room's
	Population (per thousand people)/# Procedure Room's
	Population (per thousand people)/# ED Treatment Bays
	# Critical Care Beds/# ED Treatment Bays
	Total License Beds/# ED Treatment Bays
	Population (per thousand people)/# Observation Beds
	Population (per thousand people)/# Observation Bays
	Total License Beds/# Observation Beds
	Total License Beds/# Observation Bays
	Population (per thousand people)/# Exam Rooms
	FTE MD or equivalent (PA, NP, or etc.)/# Exam Rooms
	Total License Beds/# pneumatic tube
Others	Health Care Project Cost Growth
	Health Care Delta Cost Growth
	Health Care Phase Cost Growth
	Health Care Project Phase Cost Factor

Category	Definition
Others	Health Care Delta Budget Factor
	Health Care Project Schedule Growth
	Health Care Delta Project Schedule Growth
	Health Care Project Duration Factor
	Health Care Delta Project Duration Factor
	Health Care Project Phase Schedule Growth
	Health Care Project Phase Duration Factor
	Percent Design Complete at Authorization
	Percent Design Complete prior to Const.
	Health Care Project Definition Index
	Project Definition Rating Index
	Number of RFIs Issued
	% Modularization
	% of Union Workforce (by Work Hours)
	Rework Cost Factor
	Rework Schedule Factor
	Change Cost Factor
	Schedule Change Factor
	Total Recordable Incident Rate (TRIR)
	DART (Day Away, and Restriction or Transfer) Rate
	Fatality Rate

Note: * Most CSI Masterformat divisions are used, which include divisions 01~14, 21~23, 25~28, 31~34, 41, 44, 46, and 48 (a total of 29 divisions)

Appendix 2: Use case descriptions

Use Case ID	UC-1	**Use Case Name**	Login
Created By	Jay Choi	**Last Updated By**	10/31/2016
Date Created	08/1/2016	**Date Last Updated By**	Jay Choi

Actor	User
Description	User logs into the system by providing username and password.
Preconditions	1. User has developed 3D models using BIM authoring software and all the models (e.g., architectural, MEP, structural, and equipment) created for the project has been federated. 2. User has installed a model-based benchmarking software. 3. User's identity has been authenticated by CII. 4. The computer that the models is running is online.
Postconditions	1. User has been logged in to the system. 2. System displays the general project information screen.
Normal Course	1.0 Log in to the system 1. User starts the application by pressing the "CII" button under add-in menu. 2. System displays the login browser. 3. User enters a username and password. 4. User presses a "Log in" button. 5. System verifies the information using CII benchmarking user account data. 6. System informs the user that he/she is logged in to the system. 7. System displays the "project general information" screen.
Alternative Course	None
Exceptions	1.0. E. 1 Log in fails (at step 5) 1. System fails to verify user's account data because of an inaccurate username or password, or unavailable CII credential. 2. A message is printed on the screen, which notifies "Your username or password is incorrect. Please try again or contact CII for assistance" 3. Return to step 3. 4. If log in fails after three tries, the system terminates use case.
Special Requirements	None

Use Case ID	UC-2	**Use Case Name**	Enter PJT Information
Created By	Jay Choi	**Last Updated By**	10/31/2016
Date Created	08/10/2016	**Date Last Updated By**	Jay Choi

Actor	User
Description	User provides general project information, e.g., project name, location, type, and forecasted total project cost and schedule, which is asked on the general project information tab/screen.
Preconditions	1. User has been logged in to the system. 2. User's glossary for the questions has been linked to the system.
Postconditions	1. System receives data generated from UC-2 as well as UC-3. 2. System recognizes which variables are available or not. 3. System distinguishes available metrics from the list of HC benchmarking metrics based on metric definitions. 4. System displays a metric selection tab/screen with the information about which metrics are available, and user chooses metrics from the list of available metrics.
Normal Course	2.0 Enter project information 1. User provides answers to the questions to the best of his/her knowledge. The questions include project name, project location (city, state, and country), project nature, project type, project delivery method, actual project start date, forecasted project end date, forecasted total project cost, and forecasted building construction cost. (Note: the list of questions would be further expanded whenever necessary.) 2. User presses the "Finish" button after finishing entering data.
Alternative Course	2.1 Refer to glossary (at step 1) 1. User may press "Question mark" button placed on the right upper side for his reference to the questions. 2. System displays a reference tab with a new browser/tab. 3. User closes the reference screen/tab.
Exceptions	2.0.E.1 Close project information screen (at any steps) 1. User closes the project information tab by pressing "close" button on the upper right side of the screen. 2. System terminates use case without saving data, and the screen disappears.
Special Requirements	Question types 1. String (textbox): Project name, location, actual project start date, forecasted project end date, forecasted total project cost, and forecasted building construction cost 2. Radio button (or dropdown): project nature, project type, and project delivery method Glossary 1. User glossary provides user with definitions of key terms used in the system. 2. The glossary can be a word document downloadable from the browser by pressing "Question Mark" button.

Use Case ID	UC-3	**Use Case Name**	Process 3D Model Data
Created By	Jay	**Last Updated By**	8/23/2016
Date Created	08/11/2016	**Date Last Updated By**	Jay Choi

Actor	Modeling Software
Description	System processes data stored in 3D models according to the list of variables required for evaluating metrics. The processed data is aggregated to a single number representing the values of variables.
Preconditions	1. 3D models have been opened and is running. 2. User has been logged in to the system. 3. 3D models have been federated, i.e., all the individual models need to be linked except for duplicate ones. 4. User has finished entering data in general project information tab.
Postconditions	1. System receives data generated from UC-3 as well as UC-2. 2. System recognizes which variables are available or not. 3. System distinguishes available metrics from the list of HC benchmarking metrics based on metric definitions.
Normal Course	3.0 Extract Data 1. System requests to extract data required for metric evaluations from 3D models. 2. Modeling software returns the data to system 3. System transforms or aggregates the data in a proper format.
Alternative Course	None
Exceptions	None
Special Requirements	Below is the information may be extracted from models and transformed as examples. This list would be expanded in accordance with additional metrics included.

Category	Data	Category	Data
Medical Equipment	# Total Licensed Beds	Area/Space	BGSF
	# C.T.		Department GSF
	# MRI	Rooms	Cold Shell SF
Material Quantity	Concrete Quantity (CY)		Roof Gardens SF
	Steel Quantity (Ton)		# Operating Rooms
	Glazing Quantity (SF)		Operating Room SF
	Masonry Quantity (SF)		# Procedure Rooms
	Piping Quantity (LF)		Procedure Room SF
	HVAC Quantity (LF)		

Use Case ID	UC-4	**Use Case Name**	Determine Available Metrics
Created By	Jay	**Last Updated By**	
Date Created	11/1/2016	**Date Last Updated By**	11/15/2016 Jay Choi

Actor	None
Description	System receives data generated from both UC-2 and UC-3 and saves the data with a unique variable ID assigned to each variable. System identifies available metrics from the list of HC benchmarking metrics, based on metric definitions that shows the relationships between metrics (metric ID) and variables (variable ID). System displays available metrics in a different format (e.g., color or shading) on metric selection tab/screen.
Preconditions	1. User has provided general project information asked on the general project information tab. 2. User has pressed the "Finish" button after finishing entering data on the general project information tab. 3. System has extracted data stored in 3D models according to the list of variables required for evaluating metrics. 4. The extracted data is aggregated to a single number representing the values of variables. 5. System has sent data generated from UC-2 and UC-3.
Postconditions	1. User selects the metrics that he/she wants to benchmark, from the list of available metrics on a metric selection screen.
Normal Course	4.0 Determine Available Metrics 1. System receives data from general project information (UC-2) and 3D model data (UC-3) 2. System temporarily saves the data in a server, and checks which metrics are measurable using given data. 3. System distinguishes available metrics from all the metrics, and displays available ones in a different format on metric selection screen/tab.
Alternative Course	None
Exceptions	4.0.E.1 No available metrics exist (at step 3) 1. System informs user that no metrics are available with the model. 2. System asks user if he would like to terminate the system. 1. If user says yes, system terminates use case and the software closes.
Special Requirements	Metric definitions are presented in Appendix 1.

Use Case ID	UC-5	**Use Case Name**	Select Metrics
Created By	Jay	**Last Updated By**	11/1/2016
Date Created	08/11/2016	**Date Last Updated By**	Jay Choi

Actor	User
Description	User selects the metrics to benchmark, from the list of available metrics on a metric selection screen. User can navigate available metrics by metric category, which includes cost metrics, schedule metrics, dimensional metrics, material use efficiency metrics, and planning metrics.
Preconditions	1. System receives data from general project information (UC-2) and 3D model data (UC-3) 2. System temporarily saves the data in a server, and checks which metrics are measurable based on given data. 3. System distinguishes available metrics from all the metrics, and displays available ones in a different format on metric selection screen/tab.
Postconditions	1. System consolidates metrics that user selected. 2. System detects which data (i.e., variables) are required for the selected metrics. 3. System send required data to CII.
Normal Course	5.0 Select Metrics 1. System displays the list of metrics by their category which are cost, schedule, dimensional, planning, and design efficiency. 2. User selects metrics among available ones by navigating them by category. 3. User confirms that all the metrics to benchmark were selected by pressing “Finish” button.
Alternative Course	None
Exceptions	5.0.E.1 No metrics are selected (at step 3) 1. System informs user that no metrics are selected. 2. System asks user if there is no metrics to benchmark. 3. If user says yes, system terminates use case. If user says no, go to the step 1.
Special Requirements	Metric categories are presented in Appendix 1. When this use case is terminated, data will be saved in CII database.

Use Case ID	UC-6	**Use Case Name**	Send Data to CII
Created By	Jay	**Last Updated By**	11/1/2016
Date Created	08/16/2016	**Date Last Updated By**	Jay Choi

Actor	Modeling Software and CII
Description	System consolidates metrics that user selected from UC-5 and identifies which data (i.e., variables) are required for evaluating the selected metrics. System sends required data to CII Healthcare Benchmarking database.
Preconditions	1. User has selected metrics to benchmark. 2. User has confirmed that all the metrics to benchmark were selected by pressing "Finish" button.
Postconditions	1. CII receives data that system sent and stores the data in CII Healthcare Benchmarking database. 2. CII calculates metric scores for all the selected metrics (by user) of all projects saved in the database. 3. CII sends the metric scores to system 4. System receives metric scores from CII.
Normal Course	6.0 Send Data to CII 1 System recognizes a list of metrics that user selected. 2 System decides which data (i.e., variables) are required for the selected metrics. 3 System send the required data to CII Healthcare Benchmarking database.
Alternative Course	None
Exceptions	None
Special Requirements	Data exchange between system and CII Healthcare Benchmarking database will be done by API (Application Programming Interface).

Use Case ID	UC-7	**Use Case Name**	Receive metric values from CII
Created By	Jay	**Last Updated By**	
Date Created	08/16/2016	**Date Last Updated By**	11/1/2016 Jay Choi

Actor	CII
Description	The metric scores of all the project stored in CII HC Benchmarking database are sent to system in this use case. System identifies outliers among the metric values that CII sent and excludes the cases. System also re-calculates quartiles and other descriptive statistics without outliers.
Preconditions	1. System has consolidated metrics that user selected, and detected which data (i.e., variables) are required for the selected metrics. 2. System has sent required data to CII Healthcare Benchmarking database. 3. All of the data has been consolidated into a standard format in accordance with CII HC database structure and stored in the database. 4. CII has calculated metric scores of those that user had selected, for all the projects in the database. 5. CII has sent the metric scores to system
Postconditions	1. System plots quartile charts for metrics. 2. System opens "Report" in a new browser/tab, which contains quartile charts and relevant information regarding the charts. 3. User views a report that have benchmarking outcomes of the selected metrics. 4. User terminates the system by pressing "Finish" button.
Normal Course	7.0 Receive metric values from CII 1. System receives metric scores from CII. 2. System generates quartiles for each metrics, and calculates IQR 3. System remove outliers which are any values lying more than 3 times the IQR below the first or above the third quartile. 4. System generates quartiles for each metrics and conducts descriptive statistics (i.e., 1st, 2nd, and 3rd quartiles, mean, and minimum and maximum).
Alternative Course	None
Exceptions	None
Special Requirements	Data exchange between system and CII Healthcare Benchmarking database will be done by API (Application Programming Interface).

Use Case ID	UC-8	Use Case Name	View Report
Created By	Jay	**Last Updated By**	11/8/2016
Date Created	08/14/2016	**Date Last Updated By**	Jay Choi

Actor	User
Description	User receives benchmarking outcomes of the metrics that they chose. The reports include quartile graphs and relevant quartile information. Optionally, system allows the user to print out the report and save report in a PDF.
Preconditions	1. User has selected a set of metrics that he wants to benchmark. 2. User has clicked "Finish" button on the "Select Metrics" tab. 3. Metric values have been received from CII.
Postconditions	1. System asks if user would like to log out.
Normal Course	8.0 View Report 1. System plots quartile charts for metrics. 2. System opens "Report" in a new browser/tab, which contains quartile charts and relevant information regarding the charts. 3. User views a report that have benchmarking outcomes of the selected metrics. 4. User presses "Finish" button.
Alternative Course	8.1 Print Report (after step 3) 1. User clicks "Print" button. 2. System prints out a report. 8.2 Save Report (after step 3) 1. User clicks "Save" button. 2. System asks where to save the report in his computer. 3. User designates a place to store the report.
Exceptions	None
Special Requirements	Necessary functionalities for saving and printing a benchmarking report 1. Each of "Save", "Print" button to run alternative course of the use case.

Use Case ID	UC-9	**Use Case Name**	Log out
Created By	Jay	**Last Updated By**	11/8/2016
Date Created	08/16/2016	**Date Last Updated By**	Jay Choi

Actor	User
Description	User clicks on "Logout" and system is terminated.
Preconditions	1. User views a report that have benchmarking outcomes of the selected metrics. 2. User presses "Finish" button.
Postconditions	1. System is terminated.
Normal Course	10.0 Log out 1. User clicks on the logout button. 2. System informs the user that he/she is logged in to the system. 3. System is terminated
Alternative Course	None
Exceptions	None
Special Requirements	None

Use Case ID	UC-10	**Use Case Name**	Registration
Created By	Jay	**Last Updated By**	11/1/2016
Date Created	08/16/2016	**Date Last Updated By**	Jay Choi

Actor	CII
Description	CII activates or deactivate users' account. User's account is managed in this use case.
Preconditions	None
Postconditions	1. User log in to system using username and password.
Normal Course	11.0 Registration 1. CII is logged in to CII user account database. 2. CII creates an account for user by user's request. 3. CII saves the account information in the database. 4. CII closes the user account database. 5. User has username and password to access the system.
Alternative Course	11.1 User account management (from step 1) 1. CII updates or deletes user's account when necessary. 2. CII is logged out from the database.
Exceptions	None
Special Requirements	User account information may be downloaded from the system.

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