**Journal of Information Systems Engineering and Management**
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

# Integrating Design Management Practices to Improve Buildability in Construction Projects

[1]Md. Tamzidul Alam Chowdhury, [2]Bipul Dutta, [3]Mehedi Hasan, [4]Bithika Shabnam Bithi, [5]Md. Amit Hasan

[1]Department of Technology Management, Avila University, Kansas City, MO 64145, USA

[2]Computer Science and Engineering, Bangladesh University, Dhaka 1207, Bangladesh.

[3]Faculty of Business Studies, Jagannath University, Dhaka 1100, Bangladesh.

[4]Department of Computer Science and Engineering, Atish Dipankar University of Science & Technology, Dhaka 1230, Bangladesh.

[5]Department of Computer Science and Engineering, Bangladesh University of Business and Technology (BUBT), Dhaka 1216, Bangladesh.

**ARTICLE INFO**

Received: 02 Nov 2023

Accepted: 25 Dec 2023

**ABSTRACT**

The integration of design management practices plays an important role in improving the buildability of building projects. The main focus of this study is on the design decisions, including the task time, resource allocation, and the material choices, in terms of the time and the cost during project development. Data on the quantitative design are used, with machine learning (Random Forest (RF), Support Vector Machines (SVM) and Gradient Boosting (GBM) as well as Monte Carlo Simulations (MCS) to identify the risks and predict the buildability outcome. The research suggests the most significant factors affecting project delay are the task duration and the cost. The Random Forest model has the highest predictive ability ($R^2$ = 0.67) with regard to predicting the buildability. The findings emphasise the importance of early-stage design management to minimise risks, improve time schedule fulfilment and reduce costs. The application of modern data analysis techniques will help practitioners make reasonable design decisions that will lead to better buildability and project success. This research also contributes to the body of knowledge in construction project management as it will offer evidence that shows the value of data-driven solutions to improve buildability.

Keywords: Design management, Buildability, Construction projects, Machine learning, Random Forest, Support Vector Machines, Gradient Boosting, Risk analysis, Monte Carlo simulations, Task duration, Project cost, Resource allocation. or the delay of the project deliveries as unexpected

## INTRODUCTION

Design management plays a vital role in successful construction projects. It involves the systematic organisation and management of the design process from the design conception to the last construction process in order to achieve client satisfaction in terms of design, cost and time [1]. Buildability, on the other hand, is the capability of a construction project to be realised when considering a proposed design. It relates to the feasibility of construction, i.e. availability of material, constructability of the assemblies and efficiency of the construction process. A buildable design will help with the construction process, minimise risks and optimise the use of resources so that the project is completed within the set time and cost frames [2].

The influence of project design on the buildability and feasibility of construction is tremendous. Poor design decisions can result in time and cost overruns, construction delays and design-related safety risks. For instance, a complex design can require more resources or skill sets that may increase the cost and time duration of the project [3]. Also, design decisions that are not attentive to the constraints of the job site and which does not consider the local environment may result in rework problems will arise during construction. So, effective design management is suggested to be considered at the early stages of the project to overcome these issues. Involving all stakeholders (architects, contractors, clients and engineers) early in the process would ensure that any potential problems that may affect buildability are identified before the start of construction and therefore, the likelihood of a project failing is reduced [4]. Hence, effectively managing the design process, the project team would develop practical and cost-efficient designs, which in turn enhance the buildability.

A host of issues can plague construction projects, the majority of which are directly linked to design and planning. Delays, cost overruns and safety risks are often encountered. Examples of delays include in construction; a delay can occur as a result of a design change that in turn was due to an oversight or inadequate communication during the design [5]. Overbudgets are also linked to a design which does not take into consideration the size of the project, e.g. the cost of the materials is underestimated, and so are the costs of labour. The design does not take into account issues such as structural integrity and the health and safety of on-site workers, which have contributed to safety concerns. The greater part of these problems could be linked to the design management and design buildability not being integrated at the early stages of the project [6]. All it takes is a flawed approach to managing design to see the problem quickly escalate, and that can cause a lot of distraction and loss of productivity in the execution of the project.

This linkage between poor design and failure in construction justifies the effectiveness of extensive design management practices. These issues are minimised by effective design management, which can ensure the design is not only aesthetically pleasing but also economical, functional and can be built. Here, the author aims to address these problems by considering how the integration of design management practices into the project process could improve project buildability, reduce costs and ease the implementation of a project.

The primary purpose of the paper is to investigate how the adoption of design management practices impacts the buildability of construction projects. By distinguishing the relationship between design management and buildability, this research will be used to illustrate how the systematic process of running the design of a project, rather than the ad-hoc process, could lead to a more efficient, economical and safe built environment. Specifically, this paper will consider how integrating design practices during the early stages of project planning and execution may assist in identifying potential buildability issues to ensure that they are not escalated into problems that will impact the project. The effectiveness of good design management in construction will be measured in this study by using advanced data analysis techniques such as machine learning and statistical modelling.

The paper will seek to answer the following questions: What are the impacts of design management on budget, time management and project performance? Are there any data analysis models which forecast the effect of design choices on buildability? The current paper is valuable to the field of construction management, as it is bridging the new data analysis (machine learning and statistical models) tools with improving design management and buildability. While the literature so far stresses the theoretical importance of design management and buildability, in the present paper, it will be analysed and measured by data analysis in terms of its impact on construction performance. Based on real-life data, the paper offers valuable insight into the predictive capacity of machine learning models for designing feasibility and performance. This is more than an opinion about the importance of incorporating design management principles, but also a resource helping construction practitioners to optimise the designs to enhance buildability. Through these, the paper seeks to provide practically usable knowledge which can be applied to practical construction projects, so that there is a match between the theoretical design conceptualization rules and the actual determination of the construction activities.

Ultimately, the research provides a comprehensive framework for improving buildability through effective design management practices, and reveals how traditional construction management practices, integrated with modern statistical approaches to data analysis, can be harmonised. Therefore, it primes the future scientific investigations in the field of construction management, such as in the niche of data analytics and predictive modelling for optimisation of construction projects.

Journal of Information Systems Engineering and Management
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

## LITERATURE REVIEW

### Design Management in Construction:

Design management is crucial for the success of construction projects. This involves the holistic integration of the design-making processes, where the design should be related to the project objectives, time, cost and quality [7]. Ineffective design management practices are often linked with delays in construction project advancement, exceeding the cost estimate, and problems in construction quality. Available literature suggests the need for earlier involvement of all stakeholders in the design process [8]. One such strategy that is widely published is early contractor involvement (ECI), which means that when the contractor is involved in the early design of a project, it may help to mitigate potential problems associated with constructability before the construction phase. ECI helps in ensuring the functionality, constructability and optimality of the design within the constraints given, leading to more efficient design and construction [9].

Another significant strategy mentioned in the literature is value engineering (VE). VE deals with the optimisation of value; i.e. other design options are explored which provide equal or better performances but with lower costs. It advocates the notion of collaborative effort between designers, engineers and contractors to achieve cost-effective solutions without compromising quality. There are documented effects of VE on buildability, and studies have shown that VE can help reduce costs during the construction phase without compromising functionality, and even with a higher project cost [10]. By focusing on the economic and technical aspects of design, VE improves the overall buildability by ensuring designs are not only optimal in regard to functional efficiency but also economical and easier to build.

Sustainable design has also been an emerging focus of architecture in recent years. Sustainable design is a hot topic in the construction industry with increasing demands. Other research shows that sustainability should be a key feature in the management and design of projects to improve a project's buildability [11]. Sustainable design features include energy efficiency, renewable energy sources and waste minimisation. With these elements being important at the design level, it is easier to adopt an energy-conservative approach that is not only environmentally friendly, but also economical and buildable.

### Buildability and Project Success:

Buildability and project success are significant topics in construction management. Important dimensions of project success are often related to cost, time and quality (buildability). Research has shown that buildability considered in the early design phase can save significant time during the construction phase, can avoid time and budget overruns, and can enhance the success of the project [12]. For instance, a study has shown that co-operation between the designer and contractor in the early stages of mobilisation of a design reduces the likelihood of encountering an unexpected problem in the construction phase, and subsequently results in a smoother implementation process of the project [13].

Various studies have highlighted the importance of constructability, also referred to as buildability, in relation to the design process. Constructability is the ease of transitioning a design to a real construct. According to the researchers, construction professionals should analyse and inspect the constructability of designs at the early stages to avoid rework [14]. The design failures could be detected in the later stages of project execution, and will result in significant changes, thus leading to time and cost overruns. However, if constructability issues are assessed in the early stage of design, it will lead to an active and proactive management of the project to enable it to be completed on budget and on time. This will be fundamental in any project that might involve complexities during the construction phase and therefore have serious setbacks. In addition, the study has also mentioned that one of the strategies for improving buildability is through implementing constructability reviews during the design phase [15].

The other implication that is provided in the literature is that project success is not limited to time and cost criteria, but also quality. Buildability is related to the quality of the final product; poor design choices can lead to constructs with issues related to safety and final functioning. Research about the relationship between buildability and project success reveals the fact that buildability translates directly to the success of the project, in terms of efficient operation and sustainability [16]. So, a greater focus on buildability leads to the overall success of a project.

**Technological Advancements**

Technological development has hit the construction industry, particularly with the use of Building Information Modelling (BIM) and project databases. BIM (Building Information Model) is data input of the physical and functional characteristics of a building in a 3-dimensional format, and it has become a powerful design management tool. There is evidence in the literature that suggests that BIM can offer a more efficient coordination between design, engineering and construction industry, and in this way, it can assist communication and decision making [17]. BIM helps designers and contractors to imagine how potential problems will occur along the execution of the project, making it more buildable and reducing the potentiality of errors.

Data-driven project management has become increasingly important as well. Project leaders are able to optimise construction projects through the means of machine learning algorithms, predictive models and data [18]. The machine learning algorithm has been used effectively to forecast different aspects of construction projects, such as the estimation of cost, the schedule of building and resource management. For instance, predictive models could predict the impact of design choices on project schedules and costs, which could be used to inform design decisions [19]. Models can also be used to analyse the past project data in order to identify the pattern that would provide information for future practices on design management.

With the recent research, machine learning has become the new focus in the optimisation of schedules and cost prediction [20]. Machine learning models can establish the correct estimates on the duration of project completion and instances of cost incidents, along with the large amount of data from past projects. This allows construction managers to undertake pre-planned modifications in the design and planning of the construction, which ultimately leads to an increase in buildability. Additionally, risk assessment can be carried out to better understand the probability of risks, e.g., project delays or accidents, using machine learning to help the project teams to avoid potential risks at the early phase of projects [21]. The virtual presence of machine learning and data analysis tools in construction projects can be regarded as a stepping stone towards the evolution of design management, which can be more efficient and effective in executing the projects.

**Gaps in Literature**

The literature on design management and buildability is very helpful, but there are still some gaps. The lack of integration of design management and advanced data analytics for improving buildability is the first one. While various studies have discussed the benefits of design management separately, approaches such as early contractor involvement and value engineering, there has been significantly less discussion published on how these practices can be improved by using sophisticated techniques of data-based modelling, such as statistical and machine learning models.

Also, the currently available literature mostly concentrates on the conceptual models of buildability; however, they don't mention the empirical research that could demonstrate how they could apply data-driven models in practice in construction projects. This is where the aim of this paper is fulfilled. The new study will bridge the gap between the fields of theory and practice by using machine learning models and data analysis techniques in analysing the actual project data. It will provide the construction industry with valuable knowledge of how data analytics can be applied to improve the design management processes and thus enhance the buildability of a construction project.

This research will address these gaps and make a contribution to the field of construction management by introducing a new way of enhancing buildability by using design analysis within the design management process.

## METHODOLOGY

**Research Design**

The design of this study is a quantitative research design, which involves employing data analysis and statistical

**Journal of Information Systems Engineering and Management**
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
**Research Article**

models to test the extent to which design management practices have an impact on the buildability in construction projects. The focus of the first aim is to study the relationship between design management and buildability based on data from projects. The plan is for the integration of machine learning techniques to predict the effect of design on the opportunities and outcomes of construction projects. Since buildability affecting variables are quite multidimensional, this study uses the use of enhanced data analysis techniques, in particular predictive modelling and risk analysis, to produce insights.

This study uses Google Colab for the creation and analysis of the model, which is an interactive platform for coding in Python. Google Colab is very useful for this process as it provides the necessary computational processing and scalability to analyse large datasets and apply machine learning techniques. Data processing, predictive modelling and visualisation required to apply machine learning are based on Python, and there is a wide variety of libraries that can be applied in machine learning. These include: data processing with pandas, machine learning with scikit-learn and visualisation of the data and model results with matplotlib and seaborn.

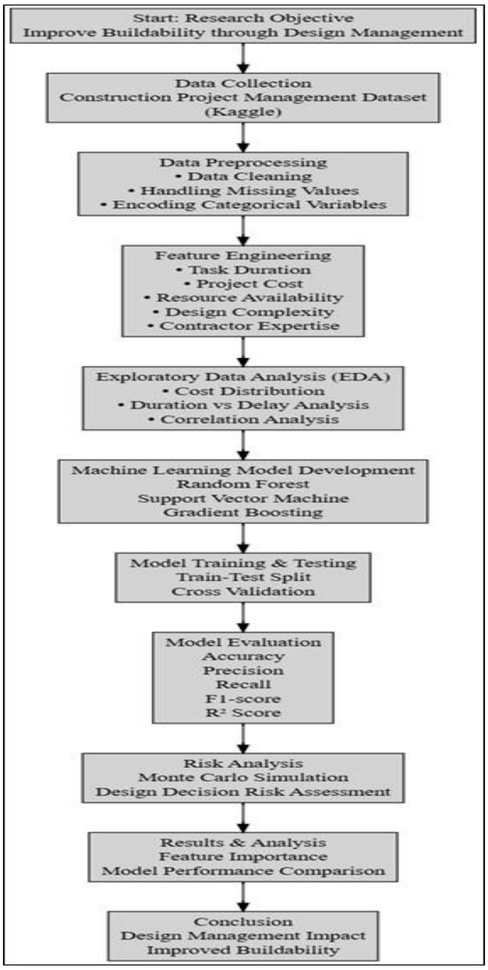


**Figure 1.** Proposed Methodology Framework

Figure 1 below shows the process of tying design management practice and machine learning to improve the buildability of construction projects. This includes data collection of the Construction Project Management Dataset, data engineering and feature engineering. It also includes exploratory data analysis (EDA), model building and training. After model evaluation and risk analysis (Monte Carlo simulations), results are applied to insights to take action and implement strategies to improve buildability by the use of data-driven design strategies.

**Data Collection**

The data used in this paper is Construction Project Management Dataset on Kaggle. This particular dataset holds one of the most comprehensive sets of project data (task times, estimates, resource allocation and project

Journal of Information Systems Engineering and Management
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

outcomes). The dataset can be used for this particular research. The attributes in the dataset are crucial to understanding the many attributes that drive the buildability of the building. For example, task time provides information about the effectiveness of design management in its impact on the project schedule. The significance of cost estimates is to gain knowledge about the effect of design decisions on the cost-effectiveness of a project. Resource allocations can also help in investigating the influence of the design phase on anticipating construction requests (in terms of material and labour resources).

The data offers a valuable opportunity to employ machine learning algorithms to evaluate the effects of the design decisions on the project in terms of cost overrun, time and safety. Using real data, this research explores the patterns and insights which would be difficult to achieve within the traditional theoretical models.

**Data Preprocessing**

Data cleaning is the first step in data pre-processing. Irrelevant, missing and duplicate data are filtered out to improve the quality of the data. Null values are dealt with in techniques of imputation, in which there may be a need to drop rows containing too many null values. For example, if 40% or more of the entries of a column are not filled, then the column can be dropped, or an appropriate imputation method (mean, median and mode imputation) can be used to preserve the columnar arrangement of data.

Moreover, nominal values such as project types, material types or others, that are used to show the type of design are encoded in either one-hot encoding or label encoding to comply with machine learning protocols. This is important so that the data can be in a form that can be fed to algorithms to be interpreted for quantitative purposes.

The next process is feature engineering, where extra features are created to capture the main factors in buildability. The design complexity can be determined in terms of the number of various design features or project demands. For instance, a design that has more complex buildability, and are hence more relevant for modelling purposes.

**Advanced Models**

To evaluate the influence of design management features on buildability, several machine learning techniques are applied, such as Random Forest, Support Vector Machines (SVM) and Gradient Boosting.

**Predictive Modelling**:

- Random Forest algorithm is used to build a collection of decision trees, which are used in creating the final prediction. This is the appropriate approach for this research because it is suitable for joining large datasets and variables with complex interactions. Random forest model will be used to identify the most influential design characteristics (e.g. duration of tasks or resource allocation) in order to predict if a project will be developed or not. The equation of a Random Forest is:

$$\hat{y}_i = \frac{1}{N} \sum_{k=1}^{N} h_k(x_i) \quad (1)$$

where $\hat{y}_i$ is the prediction for the record $i$, $h_k$ the individual decision tree model, and $N$ is the number of decision trees in the forest.

- Support Vector Machines (SVM) are one of the popular models in classification problems, where the design choices are separated into two groups, such as buildable and non-buildable. The SVM algorithm attempts to find the optimal hyperplane to separate the two groups. The mathematical representation of an SVM can be modified to maximise the margin between the two classes:

$$\text{Maximize } \frac{1}{2} \| w \|^2 \text{ subject to } y_i (w^T x_i + b) \geq 1, i = 1, \dots, N \quad (2)$$

**Journal of Information Systems Engineering and Management**
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
**Research Article**

where $x_i$ is the feature vector, $y_i$ represents the label and

w and $b$ are the hyperplane parameters.

- Gradient Boosting builds an additive model that fits the derivative (or gradient) of the model to minimise the error of the previous model. This is particularly useful for regression analysis for projects (e.g., overruns and schedule problems). The Gradient Boosting algorithm is:

$$F_m(x) = F_{m-1}(x) + \eta \cdot$$

structural design requirements would score higher in the complexity scale. Similarly, the factors such as material cost and labour efficiency are developed in a manner that

argmin

$N$

$\gamma \sum L( y_i, F_{m-1}(x_i) + \gamma)$ $i=1$

(3)

they become factors that are used to measure the amount of resources allocated towards the project. These are features engineered to represent the impact of a variety of design options and their effects on the project's

with $F_m(x)$ being the forecast of the $m-th$ model, $y_i$

being the true value and $L$ being the loss function.

**Risk Analysis**

To calculate the risk of design options, Monte Carlo simulation approaches are used to minimise the uncertainty of the construction. The model can predict the potential consequences of poor design control on the project outcome with different design inputs (e.g., costs of materials, labour, etc.) through simulations. Monte Carlo simulation is based on the following equation:

$X_{\text{outcome}}$

1 $M$

$= -\sum$

$M$ $j=1$

$f( x_j)$ (4)

where $x_j$ is the random variable inputs, $f(x_j)$ is the outcome function and $M$ is the number of iterations.

On the other hand, the application of decision trees is to classify risk, where the design decision will lead to a high-risk or a low-risk outcome in terms of cost, time and safety.

**Model Evaluation**

Once machine learning models are trained, a number of metrics, including Accuracy, Precision, Recall and F1-Score, are used to measure the quality of models. These metrics can be used as a relative measure of the model's performance so that the predictions would be accurate and provide useful advice to the design management. The Accuracy is calculated as:

**Journal of Information Systems Engineering and Management**
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

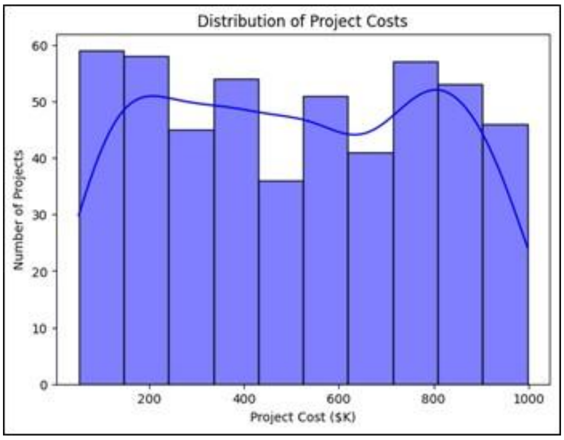


**Figure 2.** Distribution of Project Costs

The distribution of the project costs is shown in Figure 2. Most of the projects are costlier than 200,000 and less than 400,000, and the expensive projects are smaller in number. The distribution is skewed to suggest that most of the projects are likely to have similar costs, which can be used in estimating the budget of projects. Understanding the distribution of costs is important as the cost of projects impacts the design of projects, such as what materials will be chosen to organise it and its complexity, which in turn can affect the buildability of the project.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives and FN is the number of false negatives.

**Tools**

The approach is implemented using Python libraries. The data is cleaned and analysed using pandas, models are created and analysed using scikit-learn and data and results are visualised using matplotlib and seaborn, respectively. These tools allow a quick, versatile and scalable approach to data analysis, which will assist with the ability to manage big data and models.

This approach aims at combining these tools to provide a robust solution for analysing the impacts of design management practices on the constructability of construction projects, using data-driven information for construction project improvement.

## RESULTS AND ANALYSIS

### Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is an important step to get to know the type of information in the dataset and to point out trends. EDA in the current research looked at the distribution of project costs, task duration, and resource allocation and how they impact the buildability of construction projects.

**Journal of Information Systems Engineering and Management**
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

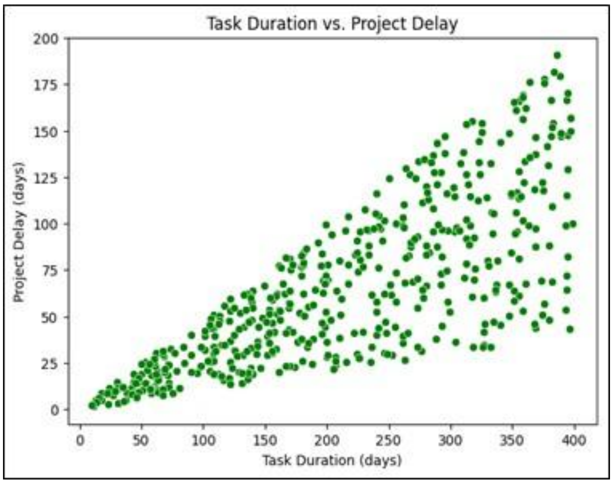


**Figure 3.** Task Duration vs. Project Delay

Figure 3 is a scatter plot of project delay and duration of tasks. The plot illustrates the positive correlation between the two, i.e. the longer the duration of the task, the larger the delay. This understanding highlights the value of time management usability in construction projects. By means of proper time management of tasks and the development of a realistic schedule, buildability can be directly improved by decreasing the likelihood of timeline and construction disruptions within construction organisations. This research study gives grounds to the hypothesis that task duration and scheduling are some of the design decisions that must be made at the onset of the project in order to maximise the performance of the project.

**Model Results**

Exploratory data analysis was then succeeded by machine learning models that approximate the impact which design options have on the constructability of construction projects. Such analysis models included the Random Forest, the Support Vector machines (SVM) and the Gradient Boosting.

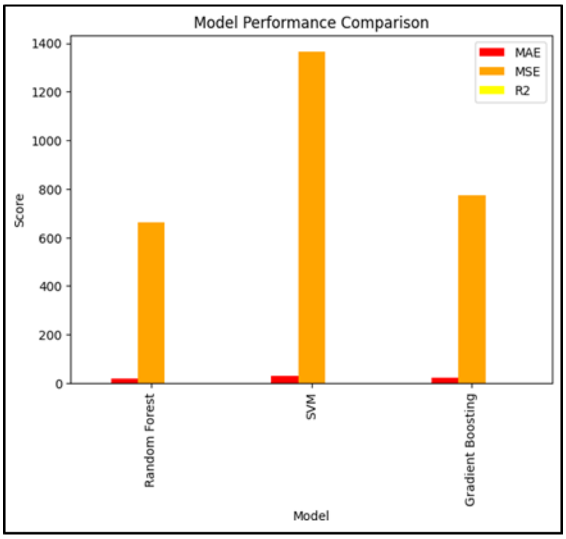


**Figure 4.** Model Performance Comparison

Figure 4 illustrates a bar chart of each model's performance individually, regarding three criteria of evaluation: Mean Absolute Error (MAE), Mean Squared Error (MSE) and R2 score. Among the three, Random Forest performed the best and has the largest R2 value of 0.67, which means that it fits the data best. This fact means that the complex decision between the variables of design and delays during the construction can be characterised with the help of Random Forest more than with the rest of the models. As with other cases, Support Vector Machines

**Journal of Information Systems Engineering and Management**
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

(SVM) resulted in a low R2 value of

0.32 and, hence, failed to fit the data as well. Gradient Boosting was also rather decent, R2 of 0.61, but would be overtaken by the Random Forest in terms of the accuracy of a prediction made.

Table 1 shows the performance of both models. The random forest model was the most accurate model based on the lowest scores on the MAE and MSE. In comparison, SVM achieves the worst error rates, which was potentially due to its sensitivity to the non-linear nature of the data.

**Table 1.** Model Performance

| Model | MAE | MSE | R2 |
|---|---|---|---|
| **Random Forest** | 19.18 | 662.60 | 0.67 |
| **SVM** | 30.13 | 1363.69 | 0.32 |
| **Gradient Boosting** | 20.65 | 772.27 | 0.61 |

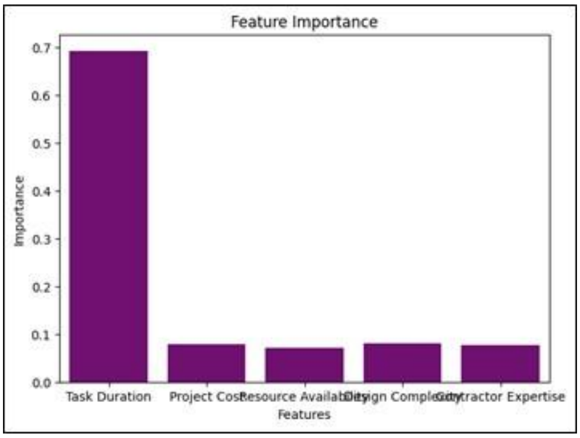


**Figure 5.** Feature Importance

Figure 5 presents the importance of the features is the outcome of the Random Forest model. This bar graph highlights the idea that the most prominent causes of delays in projects are task duration and cost of a project, followed by availability of resources and project design complexity. This means that they are critical characteristics that must be considered when making decisions in designs and are critical in predicting the results of a project.

Table 2 provides the quantitative explanation of the significance of each of the features in predicting project delays. The three variables of the greatest importance were the cost of the project and the time of the task, followed by the availability of the resource. These findings underscore the significance of proper planning of tasks and budgeting in the design stage so as to boost the overall buildability.

**Table 2.** Feature Importance

| Feature | Importanc e |
|---|---|
| **Task Duration** | 0.29 |
| **Project Cost** | 0.26 |
| **Resource** | 0.23 |

**Journal of Information Systems Engineering and Management**
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

| | |
|---|---|
| **Availability** | |
| **Design Complexity** | 0.14 |
| **Contractor Expertise** | 0.08 |

**Risk Analysis**

The risk analysis was done using Monte Carlo simulations as an attempt to give an estimate of risks that would be encountered during different design decisions. The three criteria (material costs, job timeframes, and resource availability) were evaluated as risk factors that may affect the overall construction schedule and budget.

The results of the Monte Carlo simulation, as presented in Table 3 show potential outcomes of various design options on the delay of projects. The low-cost materiality option, as well as the duration of the tasks, preconditions the occurrence of delays. On the other hand, the more resources are available and the faster the tasks take place, the better, which reduces the amount of time in which the project takes place.

**Table 3.** Risk Analysis

| Design Decision | Risk Factor | Simulation Result (Mean) | Risk Probability (%) | Impact on Project (Days) |
|---|---|---|---|---|
| **Material Choice: Low Cost** | Material Cost | $450,000 | 35% | +20 days |
| **Material Choice: High Durability** | Material Cost | $500,000 | 50% | +10 days |
| **Task Duration: Extended** | Task Duration | 120 days | 60% | +30 days |
| **Task Duratio** | Task Duration | 90 days | 40% | -10 days |

**Journal of Information Systems Engineering and Management**
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

| | | | | |
|---|---|---|---|---|
| **n : Accelerated** | | | | |
| **Resource Availability: High** | Resource Availability | 85% | 25% | -15 days |
| **Resource Availability: Low** | Resource Availability | 50% | 50% | +25 days |
| **Design Complexity: Simplified** | Design Complexity | 0.2 | 30% | -5 days |
| **Design Complexity: Complex** | Design Complexity | 0.9 | 60% | +40 days |

Concluding, a data-driven implementation of design management procedures could show a significant change in the sphere of buildability and the overall project output. By narrowing down on the key design factors, such as the time taken to complete the task and the cost, as well as the availability of the resources, the building experts are better equipped to come up with decisions that will see this project being completed within the scheduled time, on budget and to standard. Building better models to meet the concept of decision-making during the design and construction, more machine learning models and more Monte Carlo simulations are applied; there are prediction tools that are provided by the models to be applied to the construction result of guaranteed decisions.

## DISCUSSION

### Impact of Design Management Practices on Buildability

The findings of this research indicate how much the design management practices affect the buildability of building projects. By implementing a complex task- duration management and cost estimation at the earliest stage of the work, it is possible to reduce dramatically delays and bankruptcies, which are quite common in the construction business. This discussion revealed that task duration had a strong positive relationship with project delay; i.e. when there is planning or underestimation of tasks, the construction project is likely to exhibit significant amounts of delay. This is in view of other research studies, which have highlighted the importance of appropriate planning of the project and maximisation of project design in order to achieve a smoother

Journal of Information Systems Engineering and Management
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/


implementation of the project [22].

As Figure 2 of the project costs distribution and Figure 3 of the scatter plot of duration of task vs project delay demonstrates that the majority of the construction projects utilised in the data sample are similar in terms of facing challenges as far as cost and time management is concerned. A delay is likely to alter the longer task duration of projects, and the relationship shows that it is important to have control over task design in the early stages of the project to ensure that the timelines are realistic and achievable. Considering them during the design phase allows the project manager to allocate resources more efficiently as well as predict the probability of some delays in the future before it occurs, improving the overall buildability.

**Effectiveness of Machine Learning Models**

This study produced machine learning models that produce valuable data regarding how the choice of design can impact the construction project's buildability. The model which exhibited the best performance was the model which yielded the highest R2 level of 0.67, which means that it fits the data well and means that the model assumes the reality of the relationship between the design factors and the delays of the project. This finding resonates with the research that Random Forest and other ensemble models would be very suitable to develop project data, which, under the majority of circumstances, is very dimensional and non-linear [23].

On the other hand, the SVM model that reasonably performed with smaller data did not perform in the data of construction projects, which were more complex, and the R2 was 0.32. It suggests that SVM might not be the best model to draw conclusions from in the modelling of construction project data, as it has not captured the intricate relationship between the variables in this data in comparison with the Random Forest or Gradient Boosting algorithm. The Gradient Boosting results with an R2 of 0.61 value suggests the algorithm can also be used as an alternative to Random Forest; however, it is not as potent as the chosen algorithm in this case study.

**Feature Importance in Predicting Buildability**

The feature importance (Figure 4 and Table 2) has revealed that the period of a task and the cost of a project are the most important features in predicting the delay of a project and buildability. This finding suggests there is a better chance for improvement of buildability due to a design management system that tries to accurately estimate the duration of carrying out various tasks and control the costs of projects. Another significant factor is the accessible resources, and it influences the chances of finishing individual tasks within the desired duration and cost. However, although important, design complexity was found to have the least effect on the buildability issue compared to other factors. This suggests that the more complex the design is, the longer the process will be; however, the impact on the buildability can be neutralised by proper management of the time allocated to individual tasks and the amount of resources needed to complete individual tasks.

The results are in line with the literature, which considers time and cost management as an emphasis in construction [24]. Effective design management includes effective scheduling, cost estimating and resource allocation, which are construction factors that contribute to the success of construction projects. Anticipating and providing contingency against future time delays and cost increases are essential towards providing timely completion and cost savings for construction projects.

**Risk Analysis and Design Decisions**

The Monte Carlo risk analysis (Table 3) presents risks associated with design decisions. The result of the simulation shows that low-cost materials and the time of the tasks are significantly affecting the likelihood of delays, which appears to support the existing studies which are focused on the risk of using cheap materials and short time periods of projects. On the other hand, by increasing the task durations or resource amounts, it can minimise the delays, which implies that such design decisions will enhance buildability.

The other key element affecting project delays is the design's complexity. The choice of a simple design reduces the delays, as shown in the simulation findings and may delay the project (and miss the schedule) when using a complex design. This finding highlights the trade-off in functional and aesthetic design and buildability in projects [25]. While using a non-complex design might be less creative, it is more likely to be delay-free and hence, has the ability to increase buildability, along with good project management practices.

**Practical Implications of Findings**

The result of this research can be applied in practice in the construction industry. By involving design management tools and techniques during the early stages of the project, construction professionals will be able to detect the potential risks and construction problems that can arise and have them solved upfront. This can lead to better allocation of costs, realistic expectations of tasks and optimal resource allocation, which may support better performance of projects.

The application of recent techniques of data analysis, such as machine learning, during the construction phase may also yield important information and be considered in the design stage to improve the buildability of a project. Using predictive analysis, project managers will be able to predict delays and overcosting and modify the project plan accordingly, leading to better project execution.

In addition, the results of the conducted risk analysis show that it is important to take into account the prices of the needed resources, the available time for execution of the task and the resources themselves. Through data-driven decision making, construction professionals will be able to reduce risks of delays and ensure timely and cost-effective project delivery [26].

## CONCLUSION

This research has shown the impact of design management on the buildability of construction works. The present study (which used a combination of exploratory data analysis and three types of machine learning models as well as risk analysis) has demonstrated that the task duration of work on a project, project cost and resource availability are crucial factors in predicting project delays and, therefore, buildability. The Random Forest model proved to be the most valuable to understand the relationship between design features and buildability, and also as a reliable way to predict project outcomes and assist in the discovery of the most salient features, i.e., the duration of work and cost of the project.

The study of the feature importance results demonstrated that the most troublesome attributes affecting project delays are the cost and duration of tasks, which require good project and design management. The results of the Monte Carlo simulations also assisted in a better understanding of how risky some of the design decisions could be in terms of low-cost building materials or longer tasks and how these can affect the project completion time.

The possibility to merge data and information and analyse it with the help of enhanced analytics can help construction professionals get a powerful tool that can support decisions at the design stage to become more buildable and eventually improve the project's outcome. By addressing the design complexity, resources and scheduling proactively, schedule and cost overruns could be avoided, and the project would become more effective.

This research ultimately recognises the early involvement in design management in achieving better buildability and project outcomes. Risk analysis and machine learning are proving to be significant enablers in documenting design decisions, making project delivery more predictable, and enhancing the buildability of the construction process. The effectiveness of the findings can be improved and tested in future research by looking at other factors, such as environmental and stakeholder management, to 4fine-tune the design management process to improve construction project performance.

## REFERENCES

[1] E. Pikas, L. Koskela, and O. Seppänen, "Improving Building Design Processes and Design Management Practices: A Case Study," *Sustainability,* vol. 12, no. 3, p. 911, 2020, doi: https://doi.org/10.3390/su12030911.

[2] A. A. E. Othman and F. O. Alamoudy, "Optimising building performance through integrating risk management and building information modelling during the design process," *Journal of Engineering, Design and Technology,* vol. 19, no. 6, pp. 1233-1267, 2021, doi: https://doi.org/10.1108/jedt-06-2020-0246.

[3] E. Abdelbasset, A. Hassan, N. H. Amer, and Y.
A. Khalifa, "Optimizing the number of crews working in parallel and their work sequence to minimize project duration and cost for repetitive construction projects," *Innovative Infrastructure Solutions,* vol. 8, no. 11, p. 288,

2023/10/11 2023, doi: https://doi.org/10.1007/s41062-023-01233-3.

[4] I. C. Osuizugbo, K. C. Okolie, and O. O. Oyeyipo, "Factors influencing buildability assessment implementation in the Nigerian construction industry," *Construction Innovation,* vol. 23, no. 5, pp. 917-938, 2022, doi: https://doi.org/10.1108/ci-12-2021-0246.

[5] S. Durdyev and M. R. Hosseini, "Causes of delays on construction projects: a comprehensive list," *International Journal of Managing Projects in Business,* vol. 13, no. 1, pp. 20-46, 2019, doi: https://doi.org/10.1108/ijmpb-09-2018-0178.

[6] J. T. O'Connor and H. J. Koo, "Analyzing the Quality Problems and Defects of Design Deliverables on Building Projects," *Journal of Architectural Engineering,* vol. 26, no. 4, p. 04020034, 2020, doi: https://doi.org/10.1061/(ASCE)AE.1943- 5568.0000432.

[7] W. Lu *et al.*, "Design for manufacture and assembly (DfMA) in construction: the old and the new," *Architectural Engineering and Design Management,* vol. 17, no. 1-2, pp. 77-91, 2021/03/04 2021, doi: https://doi.org/10.1080/17452007.2020.176850 5.

[8] B. Perera, A. Shandraseharan, and H. Hettiarachchi, "A Framework for the Successful Implementation of Design-Build Projects: Involvement of the Stakeholders," *Bhumi, The Planning Research Journal,* vol. 9, no. 2, 2022, doi: https://doi.org/10.4038/bhumi.v9i2.81.

[9] F. Rahmani, "Challenges and opportunities in adopting early contractor involvement (ECI): client's perception," *Architectural Engineering and Design Management,* vol. 17, no. 1-2, pp. 67-76,2021/03/04 2021, doi: https://doi.org/10.1080/17452007.2020.181107 9.

[10] X. Li, C. Wang, and A. Alashwal, "Case Study on BIM and Value Engineering Integration for Construction Cost Control," *Advances in Civil Engineering,* vol. 2021, no. 1, p. 8849303, 2021, doi: https://doi.org/10.1155/2021/8849303.

[11] B. A. F. S. Barros and E. D. Sotelino, "Constructability and Sustainability Studies in Conceptual Projects: A BIM-Based Approach," *Journal of Construction Engineering and Management,* vol. 149, no. 4, p. 04023012, 2023, doi: https://doi.org/10.1061/JCEMD4.COENG- 12767.

[12] M. Calahorra-Jimenez, L. F. Alarcón, C. Torres- Machi, A. Chamorro, and K. Molenaar, "Improving cost performance in design-bid- build road projects by mapping the reasons for cost overruns into the project phases," *Revista de la construcción,* vol. 19, no. 2, pp. 334-345, 2020, doi: http://dx.doi.org/10.7764/rdlc.19.2.334

[13] M. Heidar Barghi, "Improvement of construction process by adopting lean construction principles: a construction model development," University of Birmingham, 2023. [Online]. Available: http://etheses.bham.ac.uk/id/eprint/13514

[14] G. Raviv, A. Shapira, and R. Sacks, "Empirical investigation of the applicability of constructability methods to prevent design errors," *Built Environment Project and Asset Management,* vol. 12, no. 1, pp. 53-69, 2021, doi: https://doi.org/10.1108/bepam-02-2020- 0028.

[15] P. Wimalaratne, U. Kulathunga, and T. Gajendran, "Comparison between the terms constructability and buildability: A systematic literature review," in *Proceedings of the 9th World Construction Symposium*, 2021, pp. 196-207, doi: https://doi.org/10.31705/WCS.2021.17.

[16] A. LINDERFALK and S. LJUNGQVIST, "Bridging Sustainability and Buildability in Infrastructure Projects Organisation and Sustainability Assessment in Bridge Engineering," 2020.

[17] F. M. Dinis, L. Sanhudo, J. P. Martins, and N. M. M. Ramos, "Improving project communication in the architecture, engineering and construction industry: Coupling virtual reality and laser scanning," *Journal of Building Engineering,* vol. 30, p. 101287, 2020/07/01/

2020, doi: https://doi.org/10.1016/j.jobe.2020.101287.

[18] A. Gondia, A. Siam, W. El-Dakhakhni, and A. H. Nassar, "Machine Learning Algorithms for Construction Projects Delay Risk Prediction," *Journal of Construction Engineering and Management,* vol. 146, no. 1, p. 04019085, 2020, doi: https://doi.org/10.1061/(ASCE)CO.1943- 7862.0001736.

[19] S. E. Okiye, T. C. Ohakawa, and Z. S. Nwokediegwu, "Model for early risk identification to enhance cost and schedule performance in construction projects," *IRE Journals,* vol. 5, no. 11, pp. 78-95, 2022.

[20] S. Tayefeh Hashemi, O. M. Ebadati, and H. Kaur, "Cost estimation and prediction in construction projects: a systematic review on machine learning techniques," *SN Applied Sciences,* vol. 2, no. 10, p. 1703, 2020/09/15 2020, doi: https://doi.org/10.1007/s42452-020-03497-1.

[21] D. Banerjee Chattapadhyay, J. Putta, and R. M. Rao P, "Risk Identification, Assessments, and Prediction for Mega Construction Projects: A Risk Prediction Paradigm Based on Cross Analytical-Machine Learning Model," *Buildings,* vol. 11, no. 4, p. 172, 2021. [Online]. Available: https://www.mdpi.com/2075- 5309/11/4/172.

[22] C. M. Abdullahi and M. Tembo, "Improving the efficiency and effectiveness of construction project planning and scheduling using lean principles," *International Journal of Construction Engineering and Management,* vol. 12, no. 3, pp. 75-80, 2023, doi: https://doi.org/10.5923/j.ijcem.20231203.01.

[23] M. G. Meharie, W. J. Mengesha, Z. A. Gariy, and R. N. N. Mutuku, "Application of stacking ensemble machine learning algorithm in predicting the cost of highway construction projects," *Engineering, Construction and Architectural Management,* vol. 29, no. 7, pp. 2836-2853, 2021, doi: https://doi.org/10.1108/ecam-02-2020-0128.

[24] R. A. Okereke and M. Zakariyau, "The role of construction cost management practices on construction organisations' strategic performance," *Journal Of Project Management Practice (JPMP),* vol. 2, no. 1, pp. 20-39, 2022, doi: https://doi.org/10.22452/jpmp.vol2no1.2.

[25] T. Wang, M. Abdallah, C. Clevenger, and S. Monghasemi, "Time–cost–quality trade-off analysis for planning construction projects," *Engineering, Construction and Architectural Management,* vol. 28, no. 1, pp. 82-100, 2019, doi: https://doi.org/10.1108/ecam-12-2017- 0271.

[26] K. Radman, M. B. Jelodar, R. Lovreglio, E. Ghazizadeh, and S. Wilkinson, "Digital technologies and data-driven delay management process for construction projects," (in English), *Frontiers in Built Environment,* Review vol. Volume 8 - 2022, 2022-December-21 2022, doi: https://doi.org/10.3389/fbuil.2022.1029586.