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How Does Experience with Delay Shape Managers' Making-Do Decision: Random Forest Approach

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Abstract: Making-do, a decision to start a construction task despite knowing that its preconditions are not fully ready, is a complex dilemma for construction managers. Managers' previous making-do decisions and the resulting consequence, delay, can have a significant impact on future making-do decisions. To understand how managers' experience with delay impacts their making-do decision and how it is handled differently in different countries, two surveys were administered, one in China and one in the United States (US), and 260 usable responses were collected. This study used: (1) the Mann–Whitney U test to examine whether delaying task starting time, when lacking precondition readiness, pays off with shorter delays; (2) a random forest approach to find important causes of delay that contribute to a making-do decision; and (3) an entropy-based decision tree to determine how much uncertainty in making-do decisions can be reduced by knowing managers' experience with delays in past projects. Results showed that in the United States, managers who preferred the making-do approach experienced up to 60% less task duration delay; whereas Chinese managers who preferred making-do experienced up to 100% more task duration delay due to lack of readiness in labor, equipment, material, management, and information flow. The contributions to the body of knowledge are the development of a random forest approach to quantitatively examine the relative importance of the causes of delay to the making-do decision and to reveal the fundamental differences in culture and management traditions that cause the difference between the two countries. The methods presented in this study will enable others to use a similar random forest approach repetitively for classification, prediction, and variable selection problems in civil engineering. The findings of this study will help project managers better understand underlying factors that trigger making-do decisions in China and the United States, and have more efficient collaboration and communication when they work on projects located in a foreign country. **DOI: 10.1061/(ASCE)ME.1943-5479.0000776.**

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Introduction

Making-do, a decision to start work despite knowing that the preconditions are not fully ready, has been referred to as a type of waste in construction projects (Koskela 2004). Making-do is complex and difficult to avoid, given the uncertainty of construction site management. It is also simultaneously both a rational and irrational decision (Bølviken and Koskela 2016). Although making-do is a locally and momentarily rational strategy for reducing waste, reasoning that it is better to do something than to do nothing, in the long run it can be counterproductive from the perspective of the production system, and results in waste (Bølviken and Koskela 2016). Therefore, construction managers are often faced with the dilemma of deciding how ready is ready enough to start a task when not all of the preconditions are met. The answer to this question depends heavily on the project managers' experience with previous making-do decisions. Successful experience with on-time completion when starting a task although the preconditions are not ready (making-do) encourages more such practice. On the other hand, further delays when making-do is applied adds doubt to project managers' decisions to implement making-do.

Previous research identified preconditions for the execution of tasks and emphasized the importance of precondition readiness (Ballard and Howell 1998; Koskela 2000; Jang and Kim 2008; Lindhard and Wandahl 2012; Hamzeh et al. 2015; Wang et al. 2016; Javanmardi et al. 2018), discussed triggers for making-do decisions (Koskela 2004; Formoso et al. 2011; Pikas et al. 2012; Koskela et al. 2013), and studied the impact of making-do on project performance (Formoso et al. 2011; Pikas et al. 2012; Neve and Wandahl 2018).

However, it remains unclear to what extent project managers' experience with delay shapes their future making-do decisions. The objectives of this study are to: (1) find out whether sacrificing starting time when lacking precondition readiness pays off with less duration delay; (2) identify the causes of delay and determine their relative importance and contribution to making-do decisions; and (3) quantify the amount of uncertainty that can be reduced in making-do decisions by knowing managers' delay experience associated with various causes.

In order to address the research objectives, surveys were administered to government projects performed by civilian contractors in China and the United States (US). The survey in China was distributed to 16 construction projects in Shandong Province in 2018 and collected 141 usable responses. The survey in the US was distributed to 260 companies nationwide and collected 119 usable responses (Wambeke et al. 2011). Based on the responses, the Mann-Whitney U test was used to discover whether there was a significant difference in duration delay experienced by managers who chose making-do and those who did not. Using managers' experience with starting time and duration delay as inputs and managers' making-do preferences as outputs, important causes of delay and their contribution to a making-do decision were identified.

Theoretical Framework for Making-Do and Point of Departure

There is a lack of a coherent, consistent theoretical framework to guide construction professionals as to what contributes to making-do decisions or how experience with delay shapes managers' decisions on making-do. Developing the theoretical framework will support development of better approaches to managing production and workflow within and across construction projects. Although the concept of flow is well defined and theories of flow were extensively developed in manufacturing (Sacks 2016), it is not the case in construction. For example, the *Theory of Swift* (Shingo and Dillon 1989), *Theory of Constraints* (Goldratt 1997), and *Even Flow* (Schmenner and Swink 1998) all provide sound advice for designing and managing manufacturing workflow. However, progress in the development of a theory of workflow and making-do management is delayed in construction. Inspired by *Factory Physics* (Hopp and Spearman 1996), Bertelsen et al. (2006) introduced Construction Physics as a comprehensive way of understanding construction process from a flow perspective. It emphasizes the seven prerequisite feeder flows. Koskela (2000) proposed seven preconditions for the smooth execution of construction tasks: (1) external conditions (i.e., weather), (2) equipment availability, (3) labor availability, (4) material availability, (5) prerequisite work readiness, (6) space availability, and (7) design and working method clarification. Lindhard and Wandahl (2012) recommended two additional preconditions, safe working condition and known working condition. Koskela (2004), Formoso et al. (2011), Pikas et al. (2012), and Koskela et al. (2013) discussed triggers for making-do decisions. Formoso et al. (2011), Pikas et al. (2012), and Neve and Wandahl (2018) studied the impact of making-do on project performance. However, most of the research is descriptive in nature and does not provide a way of making quantitative assessments as to what contributes to making-do decision-making and the root causes of those factors, which has inhibited the development of theoretical framework on making-do and appropriate procedures and tools to improve project performance.

The point to departure for this study is the current theory on construction flow and research on making-do as described previously. The purposes of this study are to investigate to what extent delaying task starting time when lacking precondition readiness pays off with less duration delay; which causes of delay are perceived as important for making-do decisions; and how much uncertainty in making-do decisions can be reduced by knowing managers' experiences of delay in previous projects. Construction project managers understand and answer these questions differently based on their previous project history and perception of the consequences caused by making-do decision.

Literature Review

Making-Do

Making-do, as a waste, refers to a situation in which a task is started without readiness of all its preconditions, or the execution of a task is continued although the readiness of at least one precondition has ceased (Koskela 2004). Conceptually, making-do is the opposite of buffering. Whereas in buffering there is a positive waiting time for preconditions to get ready before starting a task, in making-do that waiting time is negative (Koskela 2004).

Formoso et al. (2011) stated that "making-do has a strong relationship with the concept of improvisation." This is because when people face a difficult and uncertain situation, they tend to use whatever resources are available to reach their objectives (Cunha 2004). There are numerous factors that influence making-do decisions; for example, perception of the state of readiness, maturity of the work (Pikas et al. 2012), maintaining profitability by utilizing resources (Koskela 2004; Pikas et al. 2012), starting the work just to get the job (Koskela 2004), and lack of trust in, and pressure from, an immediate response (Formoso et al. 2011; Koskela 2004). When choosing making-do, project managers believe that by starting early, even with the lack of preconditions, the task will also be completed earlier (Koskela 2004).

By collecting data from two case studies and performing explanatory data analysis, Formoso et al. (2011) found: (1) the most frequent types of making-do were related to the access and availability of working areas, temporary facilities, protection, and equipment and tools; and (2) the main causes of making-do were the ineffectiveness in providing adequate temporary facilities, poor management of layout, space, or both, and insufficient information. Other researchers have found an apparent correlation between excessive talking and making-do, concluding that excessive talking is a valid making-do indicator (Neve and Wandahl 2018).

Formoso et al. (2011) identified the main impacts of making-do on the performance of construction projects as material waste, poor safety conditions, and reduced motivation. Pikas et al. (2012) collected empirical data over 11 weeks at a large residential construction project. They analyzed different scenarios based on task go-no-go decisions and their outcomes (i.e., completed as planned, successful but completed late, and unsuccessful or achieved partial value). Pikas et al. (2012) found that 57% of cases (12 out of 21) in which preconditions were not fully ready, some form of making-do was attempted. Furthermore, they found that in half (50%) of the cases of making-do, tasks were stopped before completion; therefore, full value was not achieved. Neve and Wandahl (2018) actively participated in weekly Last Planner System (LPS) meetings and conducted work sampling studies on six trades for three housing refurbishment projects. They found that it is highly likely that making-do is the prevailing reason for the low productivity in refurbishment projects.

Previous research has emphasized the complexity of a making-do decision, suggested stimulating factors behind making-do decisions, and demonstrated the impact of making-do on project performance.

However, there was limited empirical research that investigated how project managers' experience with task starting and duration delay shapes their making-do decisions. Therefore, it is valuable to demonstrate to what extent managers' experiences contribute to their making-do decisions.

Construction Task Delay

Lindhard (2014) defined construction task delay as negative variation, which occurs when a work task is completed after the deadline. Wambeke et al. (2011) used variation to measure task delay and divided variation into task starting time variation and task duration variation. Burr (2016) also proposed to divide task delay into starting and duration delay. He referred to task delay as the "shift in timing of the start, or finish of a discrete critical/noncritical activity" or "an increase in the duration of a discrete critical/noncritical activity, or series of critical/noncritical activities." This study divided task delay into starting time delay and duration delay because a task delay can be caused by a delayed start, extended duration, or both. Task starting time delay is the difference between planned starting time and actual starting time. Duration delay is the difference between planned task duration and actual duration. Dissecting delay into two parts helps reveal the root causes.

Construction schedules are prone to a high level of delay due to the dynamic environment. Delay can result from: (1) external causes outside the project environment, such as extreme weather conditions (El-Adaway 2012) and nonstationary market demand (Ahmad 1999; Barriga et al. 2005), and (2) internal causes related to the project, such as workforce motivation (Han et al. 2008; Arashpour et al. 2012) and quality issues causing rework (Josephson et al. 2002; Love and Smith 2003). Wambeke et al. (2011) administered a nationwide survey in the US to identify the most prevalent causes of task starting time and duration delay. By conducting an extensive literature review, 50 causes of delay were identified and classified further under eight precondition categories. The top 10 causes of task starting time and duration delay in the US were found to be: (1) turnaround time from engineers when there is a question associated with a drawing, (2) completion of previous work, (3) obtaining required permits, (4) quality of documents (errors in design, drawings, or both), (5) rework, (6) socializing, (7) people arriving late, leaving early, or both, (8) weather impacts, (9) lack of crew skills, experience, or both, and (10) needing guidance, instruction, or both from a supervisor.

Lindhard et al. (2019) simulated 100 work tasks in 98 sequence designs and found that arranging tasks in parallel increased waste and reduced delay, and identified waste resulting from variation as an additional cause of waste. Pan et al. (2019) examined the nature of the constraints on productivity advancement in Singapore, Hong Kong, and the United Kingdom (UK). They suggested essential strategies to enhance on-time project delivery including introducing mandatory buildability and constructability framework, promoting collaborative procurement, and regulating the demand and supply of foreign labor. Antoine et al. (2019) compared the project delivery methods of US highway projects and found that procurement, studies required by the National Environmental Policy Act, and right-of-way requirements are the key contributors to project delay. Budayan (2019) studied how consultants and the public and private sectors perceived delay causes in building-operate-transfer projects in Turkey and found that the most important delay causes are related to uncertainties and changes. Private sector participants emphasized the importance of certainty on political and governmental issues. The public sector gave more weight to a detailed feasibility study and preliminary plan. Ghodrati et al. (2018) collected data from 111 general construction projects and found that communication and incentive programs have a strong positive relationship with labor productivity and project schedule performance. Tripathi and Jha (2018) collected 106 responses and found that top management competence, experience, and performance are the most important factors impacting construction organization and project success. Recent research also found that urgency; presence of a project management team in the design phase, the construction phase, or both; and management conduct and interaction have an impact on project delay and performance (Shen et al. 2018; Sun et al. 2019; Safapour and Kermanshachi 2019).

Previous research has studied causes of task delay from various perspectives. It is not clear, however, how managers' past experience with delay impacts their estimation of future delay and level of risk tolerance. It will be beneficial to understand the mechanism between experienced delay and assessment of precondition readiness for future tasks.

Random Forest

Random forest (RF) introduced by Breiman (2001) is a nonparametric supervised method of machine learning that uses an ensemble of multiple classification and regression trees (CART) for classification, prediction, and variable selection (James et al. 2013; Yeh et al. 2014).

RF has several advantages that makes it a suitable machine learning method for variable selection in this study. First, RF can handle large numbers of input variables in a relatively small sample size with missing values and avoid model over-fitting (Abdel-Rahman et al. 2013; Liu et al. 2018). Second, because RF is a nonparametric machine learning method, no assumptions are required to be made about the type of relationship between input and target variables and the distribution of those variables (Xie et al. 2017). Third, unlike a single decision tree, RF does not suffer from instability problems and it is more robust with respect to noises. Its algorithm combines and averages results across a large set of decision trees (Breiman 2001; James et al. 2013). Fourth, with specific provisions, RF can handle the multicollinearity problem among input variables (Strobl et al. 2008; Neville and Tan 2014).

Xie et al. (2017) used RF and decision tree to predict the delineation of evacuation zones in the 2050s and 2090s, based on the predicted sea-level rises and changes of demoeconomic features. Using 10% of data as the validation data set to evaluate model performance, Xie et al. (2017) found that the RF outperforms the decision tree in terms of the accuracy and Kappa statistic. Liu et al. (2018) developed three models to evaluate the impact of outdoor ambient environmental factors on scaffolding construction productivity: (1) a nonparametric regression model, (2) the generalized additive model (GAM), and (3) a nonlinear machine learning RF model. They concluded that because RF and GAM models demonstrated better performance, the relationship between outdoor ambient environment and construction productivity is nonlinear and should be built by nonlinear models. RF also has been used for predicting safety accidents caused by excavation of deep foundation pits in subway stations (Zhou and Feng 2014). Researchers found that, in contrast to artificial neural nets (ANN) and Bayesian networks (BN), RF could accurately predict the safety risks of subway foundation pits based on safety risk level monitoring values, using small and unbalanced data samples. The superiority of RF in prediction and classification has been confirmed by other research studies in construction management. Poh et al. (2018) used five machine-learning methods to predict the occurrence and severity of accidents on construction project sites based on input variables that were project-related (such as project type and percent completed) and safety inspection-related (such as crane operations, lifting operations, or both, and falling hazards, openings, or both). Those machine learning methods were: decision tree, RF, logistic regression, K-nearest neighbor (KNN), and support vector machines (SVM). During validation, it was found that RF provides the best prediction performance with an accuracy of 78%.

Based on the literature review of the performance of previous applications of RF, this study adopted the RF approach to analyze project managers' perceived delay and how it contributes to making-do decisions. The contributions to the body of knowledge are: (1) revealing construction managers' perceptions on delay and how that shapes their making-do decisions will contribute the theoretical framework development for construction flow and making-do research; (2) discovering the fundamental differences in culture and the way projects are operated will be valuable for managers working on international projects to enable more effective communication with partners in foreign countries and take meaningful actions to prevent and manage delays; and (3) developing a random forest approach to quantitatively examine how the relative importance of delay cause contributes to the making-do decision will enable other researchers to use the similar random forest approach repetitively for classification, prediction, and variable selection problems in civil engineering.

Research Methodology

Questionnaire Survey

In order to understand how project managers' perception in delay contributes to their making-do decision, the research team conducted two surveys, one in China and another in the US. Each survey included three sections. The first section asked for background information, including project location, size, and type, the type of organization to which respondents belong, the number of employees in the organization, company size, and company revenue. It also asked about the respondents' background, such as position, years of experience in construction, education, and number of subordinates. The second section asked about the respondents' preference regarding making-do, i.e., whether they prefer to start work or to wait when the preconditions (such as labor, material, and equipment) are not fully ready. The third section asked for respondents' experience with task starting time and duration delay [in terms of hours per week (h/week)] due to specified individual causes of delay. The survey for the US included 50 causes of delay and was conducted by Wambeke et al. (2011).

The research team maintained the maximum level of similarity between the surveys for China and the US, adjusting the questions as needed to suit construction projects in the destination countries. For example, the pilot study group in China suggested adding summer and autumn harvest as a factor in task starting time and duration delay. Because most Chinese construction workers are from the countryside and take about two weeks of leave during these seasons to return to their hometown to harvest, starting time and duration of construction tasks are subsequently impacted. There were 44 total causes of delay identified for the survey in China and 50 for the US.

Table 1 gives the 44 causes of task starting time and duration delay in China and the 50 causes of task delay in the US. The details on how the causes were identified, categorized, and adjusted for the research can be found in Wambeke et al. (2011). There are 34 common causes, 10 special causes in China, and 17 special causes in the US.

The survey in China was distributed to 16 Special Grade construction general contractors in Shandong Province from June 2018 to August 2018 and 141 usable responses were collected. The China Ministry of Construction issued regulations to categorize construction contractors into four grades: Special Grade and Grade A, B, and C. The Special Grade standard is the highest and requires contractors to have qualifications in net property value, adequate number of qualified managers, engineers and technicians, and records of successful completion of certain types of projects. For example, the standard for Special Grade general contractors is to demonstrate that they have net assets of at least CNY 300 million (USD 44 million), paid business tax of no less than CNY 50 million (USD 7.3 million) each year for the proceeding three years, and have at least 50 level-one registered constructors. There are a total of 28 construction general contractors (GCs) at the Special Grade level (Shandong Bureau of Statistics 2018). Sixteen GCs (57%) were randomly selected to take the survey. More than half of the surveys were conducted when the companies had annual meetings. In those meetings, project managers working in other regions of China and overseas participated the survey, which brings diverse perspectives from the managers. The survey in the US was distributed to 260 contractors working in public projects nationwide and received 119 usable responses (Wambeke et al. 2011).

Mann–Whitney U Test

The Mann–Whitney U test is a nonparametric test that compares the central locations of two populations with similar-shape distributions when there are two independent random samples drawn from these populations. The Mann-Whitney U test was chosen for this study because it is more robust than the *t*-test on nonnormal distributions with any potential outliers (Lehmann 1999). Also, instead of comparing the raw data directly, the Mann–Whitney U test compares the ranked data (Newbold et al. 2012; Norušis 2012). Mann–Whitney U's null hypothesis is that there is no difference in the central locations of the two populations under consideration, assuming the populations have similar-shape distributions. In this study, the null hypothesis is that there is no difference in the central location of experienced duration delay between the two populations, those who choose making-do and those who do not.

In order to test the null hypothesis, the Mann–Whitney U statistic and Z value are calculated using the following formulas (Newbold et al. 2012):

$$U = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1 \tag{1}$$

where U = Mann–Whitney U; n_1 = size of Sample 1 (i.e., managers who choose making-do); n_2 = size of Sample 2 (i.e., managers who choose to wait); and R_1 = sum of the ranks of Sample 1. Observations from the two samples are combined and ranked in ascending order. If there are tied observations, the average of the ranks is assigned to all of them

$$E(U) = \mu_U = \frac{n_1 n_2}{2} \tag{2}$$

where $E(U)$ = expected value of U distribution given n_1 and n_2; and μ_U = mean of the Mann–Whitney U distribution for Sample 1 and Sample 2

$$\mathrm{Var}(U) = \sigma_U^2 = \frac{n_1 n_2 (n_1 + n_2 + 1)}{12} \tag{3}$$

where Var(U) and σ_U^2 = variance of U distribution given n_1 and n_2

$$Z = \frac{U - \mu_U}{\sigma_U} \tag{4}$$

Table 1. Causes for task starting time and duration delay

Category	Cause of delay (China)	Cause of delay (US)
1. Prerequisite readiness	Obtaining required permits to start the work	Obtaining required permits to start the work
	Completion of previous work	Completion of previous work
	Quality check and prerequisites' approval	Rework being required[b]
	—	Poor quality of previous work
	—	Inspections for completed work[b]
2. Detailed design	Constructability issues in design	Design constructability
	Design changes	Errors in design or drawings
	Insufficient drawings before starting construction[a]	Turnaround time from engineers
	Long owner's response time[a]	Strict requirements[b]
	Long consultant's response time	Quality control requirements[b]
	Vague and unclear drawings details[a]	Work complexity
	Nonstandard and complex structure	Work sequence or method is not well planned[b]
	Nonspecific construction method instructions	Low degree of repetition[b]
	—	Inadequate instruction on detailed working method
3. Labor force	Summer and autumn harvest[a]	Socializing (talking with fellow workers)[b]
	Laborers were called out to other projects	Absenteeism[b]
	Not enough laborers	People arriving late, leaving early, or both[b]
	Unstable labor force	Low morale, lack of motivation, or both[b]
	Inexperienced labor	Getting moved to another job, task, or both
	—	Crew size is inadequate
	—	Personnel turnover (i.e., new employees)
	—	Experience on similar tasks (i.e., learning curve)[b]
	—	Lack of skills, experience, or both of workers, crew, or both
	—	Language barrier[b]
4. Tools and equipment	Elevator unavailability[a]	Personnel lift (no operator, not the priority, maintenance)
	Small equipment misplaced, or needing maintenance[a]	Power tools (used by someone else, maintenance)[b]
	Tower crane unavailability	Crane or forklift (unavailable, no operator, maintenance)
	Hand operated tools misplaced, or needing maintenance	Hand tools (used by someone else, misplaced, maintenance)
	Vertical transportation machinery not available	Other heavy equipment (i.e., loader) not available
	Horizontal transportation machinery not available	Personal protective equipment not available[b]
5. Material and components	Material moved twice	Material needs to be moved
	Late material delivery	Material to arrive from distributor or supplier
	Supplied material mismatch	Trying to get consumables[b]
	Incorrect material size	Error in material size
	Incorrect material quality[a]	Error in material type
6. Job site conditions	Overcrowded work area, job site congestion, or both	Overcrowded work area, job site congestion, or both
	Hard to reach work surface	Difficult access to work area
	Inconvenient layout, restricted field, or both	Site layout (i.e., distance from material storage)
	Poor traffic monitoring and control[a]	—
7. Information flow	Wait to get answer for design questions	Wait to get answer for design questions
	Geological survey does not match actual conditions[a]	Need guidance or instruction from supervisor
	Not getting guidance from the supervisor	Lack of field manager (foreman) skill, knowledge, or both
	Insufficient management staff	Coordination between different trades
	Coordination issues among activities	Overcommitment because of a tight work schedule
	Overcommitment	Foreman availability
	Team leader lacks management skills	Change in scope of work
	Plan adjustment (change in scope of work)	Foreman communication skills
	Team leader lacks communication skills	Communication between owner, engineer, or both, and project manager
	Poor communication among owner, designer, and contractor	Communication between project manager and foreman[b]
	Poor communication within the construction unit	Communication between foreman and workers
8. Weather and objective causes	Adverse weather (too cold, too hot, rainy, windy)	Weather impacts (excessive heat, cold, wind, rain)
	Objective causes (uncontrollable factors such as traffic control, noise control, night construction, and environmental management)[a]	

[a]Only for China.
[b]Only for the US.

Eq. (4) is used to calculate the Z value, which is used to determine whether to reject or accept the null hypothesis according to the chosen significance level of α. In this study, α is set at 0.05, which is the probability of rejecting the null hypothesis when the null hypothesis is true.

Random Forest

The RF approach was used to identify the important causes of delay, which contribute most to reducing uncertainty in making-do decisions. Fig. 1 shows the RF structure adopted for this study, given an input–output dataset for n respondents. For example, the

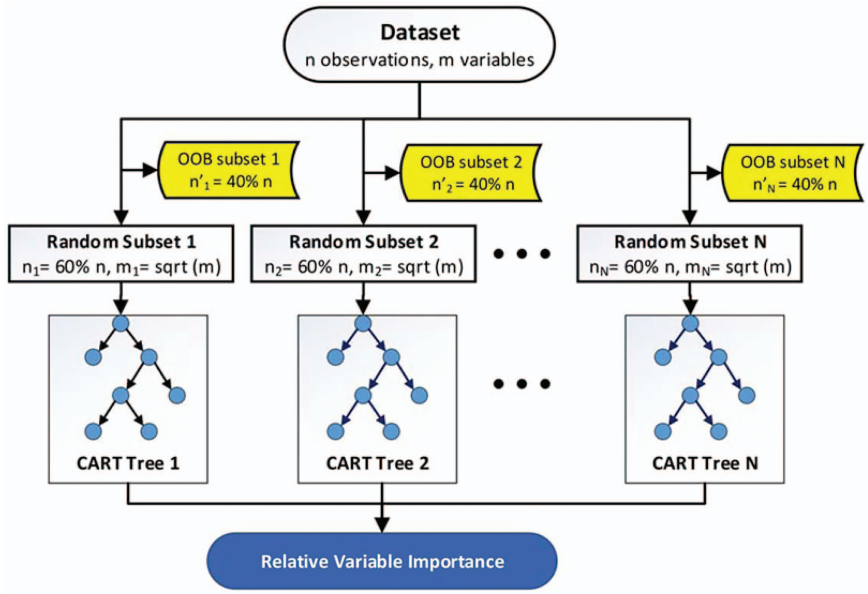

Fig. 1. (Color) RF model for variable selection.

141 responses from China included 88 continuous inputs (44 experienced weekly starting time delays and 44 duration delays) and one binary output (making-do decision: yes or no). The RF algorithm was implemented in the following steps as shown in Fig. 1 (Breiman 2001; Adusumilli et al. 2013; James et al. 2013):

1. Randomly select 60% of the total available responses to grow a tree. For the China survey, 60% of the total of 141 responses was approximately 85. The remaining 56 responses are called an out-of-bag (OOB) sample and are used subsequently for variable selection.
2. Take the square root of the number of input variables to determine the number of candidate variables to build a tree. For example, the number of input variables for the China survey was 88 and the candidate variables used to build a tree was $9 \simeq \sqrt{88}$.
3. Grow the tree using 85 randomly selected observations. To grow a tree, the first step is to split a node by finding the best splitting value for each of the nine randomly selected inputs using the Gini Impurity Index, and then select the best input among all inputs to split making-do values. For binary targets, the Gini Index simplifies to $2\hat{p}_j(1-\hat{p}_j)$, where $\hat{p}_j$ is the proportion of the responses that fall into class j of the node under consideration. Pure node has a Gini Index of zero. The process is repeated until a tree is built to the maximum depth of five.
4. Repeat Step 3 until the specified number of trees (in this case 100) are grown.

This study used the random branch assignments (RBA) (Neville and Tan 2014) method to compute the importance of causes of task delay with respect to their ability to correctly classify the making-do decisions. The main reason for using RBA was that its algorithm captures the true classification power of each input variable by handling multicollinearity and avoiding bias towards correlated input variables (Neville and Tan 2014).

The RBA method was implemented through the following steps:

1. Classify OOB responses associated with each tree in RF.
2. Calculate the margin for each node, ω, in each tree. In the case of a categorical target variable, margin is defined as "the probability of the true class minus the maximum probability among the other classes" (SAS Institute Inc. 2017). Margin can be calculated using Eq. (5) (SAS Institute Inc. 2017; Breiman and Cutler 2003)

$$\text{Margin}\,(\omega) = \sum_{j=1}^{J} N_j(\hat{p}_j - \max_{k\neq j}\hat{p}_k) \qquad (5)$$

where ω is an internal node of bth decision tree in the forest; J is the number of classes in the categorical target variable (i.e., for the binary making-do target $J=2$); j is a class of node ω; N_j is the number of responses (observations) that fall into class j of node ω; $\hat{p}_j$ is the proportion of the responses that fall into class j of node ω; k indicates other classes than j in node ω; and $\hat{p}_k$ is the proportion of the responses that fall into class k of node ω. It should be mentioned that "a good model increases the margin" (SAS Institute Inc. 2017). The algorithm steps for evaluating variable importance are as follows:

1. Calculate margin increase for each tree. The amount of margin increased by a tree is the difference between the margin of its root node (first node) and sum of the margins of its leaf nodes (end nodes).
2. Randomly assign OOB responses to the child nodes split by the variable, k. The proportion for random assignment is the same as the proportion of the observations that have fallen into child nodes of the training tree split by the variable k.
3. Repeat Steps 1 and 2. Recompute the increase of margin for each tree.
4. Calculate the difference between the original OOB margin increase and the new OOB margin increase for each tree. The new OOB margin increase would be almost certainly less than the original OOB margin increase. This reduction in margin increase is called margin reduction.
5. Average the margin reduction for the variable, k, over all trees in RF.
6. Repeat Steps 4–5 for every input variable, k. The input variables which result in the greatest margin reduction (greatest increase in error) when they are involved in RBA are the most important input variables.

This process assigns a RBA margin reduction value to each of the causes of task starting time and duration delay, which represents the relative importance of the causes of task delay for making-do decisions.

Entropy and Information Gain

This study used the information theory method to analyze the uncertainty reduction in making-do due to the amount of delay in each cause. Entropy was calculated to measure the level of uncertainty. The entropy of a random variable X, $H(X)$, is a measure of uncertainty (or impurity) in the variable. Entropy is defined as follows (Shannon 1948):

$$H(X) = \sum_{i=1}^{m} p(x_i) \log_2 \frac{1}{p(x_i)} \text{bits} \tag{6}$$

where X = a discrete random variable with m possible outcomes of x_i; and $p(x_i)$ = probability for the random variable, X, to have the value of x_i, $x_i \in \{x_1, x_2, \ldots, x_m\}$. Because entropy uses log base 2, the units are binary digits (bits). The maximum entropy for a random variable, X, with two possible outcomes (i.e., a binary variable) is 1.00 bit, which occurs when there are equal numbers of observations for each of the two possible outcomes in the data set [or the two possible outcomes have equal chance (50% probability) of happening] (Kelleher et al. 2015). The minimum entropy for a random variable, X, with two (or more) possible outcomes is 0 bit, which occurs when all the observations in data set have the same value for X.

By calculating entropy values for the input variables, the amount of information gained from each input variable will be able to be measured. In the context of this study, information gain measures the amount of information a cause of task delay provides about the making-do decision outcome. To calculate information gain from splitting a node in decision tree, entropy of the parent node (the node to be split) is compared with the entropy of the child nodes using Eq. (7) (Alfaro et al. 2019):

$$\Delta H(\omega, j) = H(\omega) - \sum_{\nu=1}^{k} \frac{N_\nu}{N} H(\omega_\nu) \tag{7}$$

where ω = parent node in a decision tree; j = input variable used for splitting ω; $\Delta H(\omega, j)$ = information gained from splitting ω and is entropy of the parent node (ω); k = total number of child nodes (for a binary split, $k = 2$); N = number or responses (observations) in the node ω; N_ν = number or responses in the child node; ω_ν = proportion of responses in node ω in which variable j takes the value ν and therefore falls into the child node, ω_ν; and $H(\omega_\nu)$ = entropy of the child node ω_ν. The second part in Eq. (7) is the expected amount of uncertainty (impurity) after splitting the responses in node ω using the input variable j. Input variables that result in more information gain are more important for predicting or classifying the target variable. If an input variable is used in more than one split in the decision tree, the total information gained by the input variable is equal to the sum of information gained from each split. In this study, information gain measures the extent to which managers' experience of task starting time and duration delay contributes to the uncertainty reduction in their making-do decisions.

Analysis and Results

The research team collected 260 responses in China and 240 responses in the US. A two-step approach was taken to clean the data and identify the usable responses. First, responses with less than 25% of the questions answered were removed. Second, the three-times interquartile range (3×IQR) was used as a cut-off point for removing outliers (Iglewicz and Hoaglin 1993). As a result, 141 and 119 useable responses were identified for the surveys in China and the US, respectively.

Research Objective 1: Test Hypothesis That Managers Who Choose Making-Do Experience Significantly More Duration Delay

The Mann-Whitney U test was performed to determine whether there are significant differences in the duration delay experienced by managers who choose making-do and those who do not. Table 2 gives the significant differences in the duration delay from nine causes experienced between the making-do and non-making-do groups in China. The making-do group experienced higher duration delay for the nine causes as follows: (1) inexperienced labor,

Table 2. Average duration delay comparison based on making-do decision

Cause of delay	Country	Average duration delay making-do (hour/week)	Average duration delay not making-do (hour/week)	*P*-value (Mann-Whitney U)
Inexperienced labor	China	1.15	0.71	0.026
Horizontal transportation	China	0.53	0.35	0.040
Late material delivery	China	0.97	0.57	0.019
Supplied material mismatch	China	0.50	0.26	0.010
Incorrect material quality	China	0.65	0.43	0.029
Insufficient management staff	China	0.58	0.44	0.029
Overcommitment	China	0.91	0.60	0.042
Poor communication between owner, designer, and GC	China	0.88	0.73	0.044
Poor communication inside construction unit	China	0.55	0.30	0.042
Obtaining required permits	US	0.16	0.00	0.023
Design changes	US	0.91	2.27	0.000
Vague and unclear drawings details	US	0.37	0.96	0.006
Nonstandard and complex structure	US	0.86	1.81	0.031
Nonspecific construction method instruction	US	0.90	1.73	0.013
Socializing	US	1.06	1.59	0.047
Absenteeism	US	0.99	1.70	0.050
Low morale and lack of motivation	US	0.39	0.74	0.042
Getting moved to another job, task, or both	US	0.89	2.11	0.005
Experience on similar tasks	US	0.61	1.37	0.003
Hand tools	US	0.17	0.40	0.011
Difficult access to work area	US	0.72	1.19	0.024
Poor communication between owner and project manager	US	0.63	1.11	0.038

(2) horizontal transportation, (3) late material delivery, (4) supplied material mismatch, (5) incorrect material quality, (6) insufficient management staff, (7) overcommitment, (8) poor communication between owner, designer, and GC, and (9) poor communication inside construction unit. Overall there are usually adequate resources available to resolve problems from the nine cases in a timely manner. Therefore, it is considered worthwhile to wait until a task is ready to be started. For example, although there has been a trend toward skilled labor shortages in the Chinese construction industry, labor dealers still have multiple resources to obtain and allocate labor quickly with short notice. In China, labor dealers have long-term partnerships with various types of specialty trades. When one project needs more labor, dealers can allocate their workers to a job site in hours. In addition, labor dealers collaborate and share workers when needed. They can also hire freelance laborers from a labor market. Therefore, when a project lacks experienced labor, waiting until laborers are ready is practical. Adding more skilled laborers reduces delay. In terms of a horizontal transportation problem, the GC usually has adequate site managers and engineers ready to resolve the problem. Regarding issues related to material (delivery, mismatch, quality), a large GC usually provides materials and has its own material department, which orders materials in large quantities. They are very selective when choosing suppliers, who are also motivated to resolve problems in a timely manner to maintain a good relationship with the GC for future business.

In the US, the results are the opposite. Managers who preferred making-do experienced significantly less duration delay as a result of the 12 causes given in Table 2. The only exception is obtaining required permits. The US managers who choose making-do experienced up to 60% less duration delay as compared to managers who did not choose making-do.

Research Objective 2: Determine Relative Importance of Delay Causes' Contribution to Making-Do Decisions

The data set for China included 88 input variables (44 for starting time delay and 44 for duration delay) and one binary output variable (making-do, 1 for yes, and 2 for no). The data set for the US included 100 input variables and one output variable. The goal was to find which input variables (causes of delay) provided more information about the values of the output variable (making-do).

In the first step, RF was utilized to select the important causes of delay with respect to making-do. SAS Enterprise Miner (EM) 14.2 was used to run the RF algorithm. Fig. 2 shows the relationship between the number of input variables used in the tree model and the performance of the tree model, which was measured by the misclassification rate. The results show that selecting the first 11 important causes reduces the misclassification rate up to 21%. Adding 77 more variables resulted in an additional reduction of 6% in the misclassification rate. Therefore, including the first 11 delay causes gives the tree model the biggest bang for the buck. For the same reason, 11 causes were selected to build the decision tree model for the US.

To evaluate the relative importance of the selected causes of task delay, this study: (1) calculated RBA margin reduction of the delay causes for both countries (RBA margin reduction column in Tables 3 and 4), and (2) scaled the RBA values by assigning 100 to the highest RBA margin reduction (Variable importance column in Tables 3 and 4).

In Table 3 the top four experienced delays that influenced making-do decisions for managers in China are lack of readiness in: (1) materials (material mismatch), (2) design and working method (insufficient drawing details), (3) labor (inexperienced workers), and (4) equipment (horizontal transport). Looking at the US results (Table 4), however, the causes of task delay that

Table 3. RF variable importance calculation based on RBA margin reduction for China

Cause of delay	Number of splitting rules	RBA margin reduction	Variable importance
Material mismatch_S	59	0.0428	100
Insufficient drawing details_ S	32	0.0278	65
Inexperienced workers_D	30	0.0258	60
Horizontal transport_D	16	0.0241	56
Material mismatch_D	22	0.0229	54
Poor communication unit_D	34	0.0222	52
Incorrect material quality_D	22	0.0196	46
Vertical transport_S	52	0.0195	45
Incorrect material quality_S	11	0.0184	43
Design change_S	29	0.0181	42
Inconvenient layout_S	22	0.0169	40

Table 4. RF variable importance calculation based on RBA margin reduction for the US

Cause of delay	Number of splitting rules	RBA margin reduction	Variable importance
Design drawing error_D	38	0.0326	100
Lack instruction work method_S	39	0.0206	63
Access_S	16	0.0202	62
Question answer time_D	39	0.0196	60
Question answer time_S	45	0.0183	56
Quality control_D	18	0.0165	51
Worker experience_ D	36	0.0161	49
Wait for answer_D	31	0.0152	47
Rework_S	26	0.0148	45
Personal protective equipment_S	14	0.0146	45
Power tools_S	11	0.0122	37

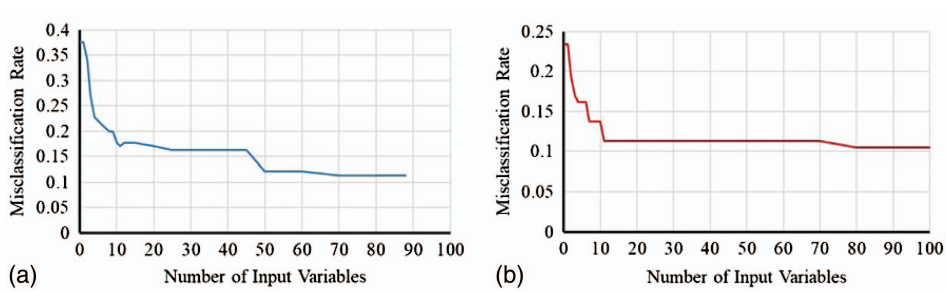

Fig. 2. (Color) Number of input variables and misclassification rate for decision tree model: (a) China; and (b) United States.

influence managers' making-do decisions are more confined. Four out of the five most important causes of delay that contribute to making-do decisions belong to readiness of the design and working method precondition, specifically the experienced amount of task starting time (identified by _S) and task duration (identified by_D) delay due to design drawing error, lack of instruction working method, and question answer time.

Research Objective 3: Quantify the Amount of Uncertainty That Can Be Reduced in Making-Do Decisions by Knowing Managers' Delay Experience Associated with Various Causes

To calculate information gained from the 11 important causes of delay identified in the previous section, two decision trees were built, one for China and another for the US. For each split in the trees, the entropy of the parent node was compared with the sum of entropies of the child nodes and the amount of information gain was calculated using Eq. (7). For example, the first split of the tree for China was made based on the amount of starting time delay experienced due to material mismatch. Using Eq. (6) the entropy of the parent node (Node 1) was equal to $H_1 = -0.6241 \times \log_2(0.6241) - 0.3759 \times \log_2(0.3759) = 0.9551$ bits, in which 0.6241 (62.41%) of respondents chose making-do and 0.3759 (37.59%) did not. Similarly, the entropy values for child nodes, H_2 and H_3, were 0.9983 and 0.4855 bits, respectively. Using Eq. (7), information gain from material mismatch_S was equal to $H1 - (103/141 \times H2 + 38/141 \times H3) = 0.095$ bits, as given in Table 5.

The amount of information gained from each of the delay causes in the related trees is given in Table 5 (China) and Table 6 (US). At the beginning before starting classification, there were 0.9551 bits of uncertainty about making-do in China and 0.7847 bits of uncertainty about making-do in US. Every time a cause of delay was used to split making-do responses, the remaining uncertainty about the making-do decision was reduced. However, the tree models could not perfectly classify making-do responses. Therefore, 0.50 bits (and 0.36 bits) of uncertainty remained about whether managers prefer making-do or not, despite knowing the amount of delay they have experienced in the past.

The results given in Tables 5 and 6 are shown in Figs. 3(a and b) to understand the extent precondition categories contribute to a making-do decision. The percentage of contribution by each precondition category to the reduction of overall uncertainty in making-do is calculated by summing the information gain of causes of delay that fall into one precondition category and dividing it by the total uncertainty in making-do.

Fig. 3(a) shows that in China, availability of materials, design and specifications, and labor are the top three preconditions influencing managers' making-do decisions. Also, Fig. 3(a) shows that 53% of uncertainty in making-do could not be explained by the amount of delay Chinese managers have experienced in the past due to lack of readiness in preconditions. The remaining uncertainty about whether a Chinese manager is going to practice making-do or not depends on other factors such as owner request, crew utilization, and similar factors that were discussed in the literature review section.

As expected from the results in the previous section, the main precondition that determines whether a manager or crew leader in the US practices making-do or not is the availability of design and working method instructions. Compared to China, precondition readiness contributes 8% more to managers, crew leaders, or both, making-do decisions because 45% uncertainty is left after the US managers' experienced delay is uncovered.

Conclusions

In order to understand how the amount of task starting time and duration delay experienced by managers influences their making-do decisions, surveys were conducted in China and in the US. Findings showed Chinese project managers are less likely to decide making-do (62% chance) compared to their US counterparts (77% chance). This could be related to the fact that making-do in China

Table 5. Uncertainty reduction in making-do by gaining information about experienced amount of delay due to the causes of delay in China

Cause of variation	Information gain (bits)	Cumulative information gain (bits)	Uncertainty (bits)	Contribution to uncertainty reduction (%)
—	—	—	0.9551	—
Material mismatch_S	0.095	0.095	0.8601	21.0
Insufficient drawing details_ S	0.0868	0.1818	0.7733	19.2
Design change_S	0.0721	0.2539	0.7012	15.9
Incorrect material quality_D	0.0721	0.326	0.6291	15.9
Inexperienced workers_D	0.0423	0.3683	0.5868	9.4
Inconvenient layout_S	0.0345	0.4028	0.5523	7.6
Incorrect material quality_S	0.0252	0.428	0.5271	5.6
Poor communication unit_D	0.0243	0.4523	0.5028	5.4

Table 6. Uncertainty reduction in making-do by gaining information about experienced amount of delay due to the causes of delay in the US

Cause of delay	Information gain (bits)	Cumulative information gain (bits)	Uncertainty (bits)	Contribution to uncertainty reduction (%)
—	—	—	0.7847	—
Design drawing error_D	0.0995	0.0995	0.6852	23.2
Rework_S	0.0821	0.1816	0.6031	19.2
Question answer time_S	0.0729	0.2545	0.5302	17.0
Wait for answer_D	0.0684	0.3229	0.4618	16.0
Lack instruction work method_S	0.0447	0.3676	0.4171	10.4
Access_S	0.0359	0.4035	0.3812	8.4
Worker experience_D	0.0247	0.4282	0.3565	5.8

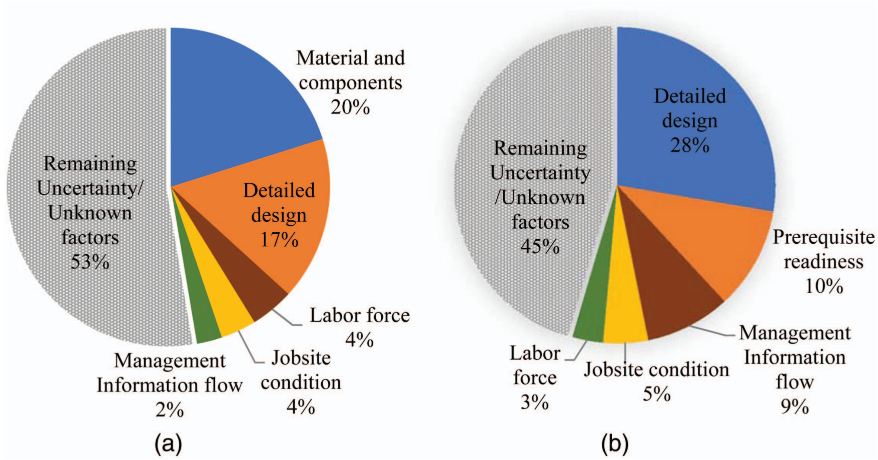

Fig. 3. (Color) Contribution of precondition categories to making-do: (a) China; and (b) United States.

results in duration waste. Project managers in China, who prefer making-do in situations where material, labor, and equipment are not ready and the management, information flow system, or both, are ineffective have experienced, on average, two times more delay than project managers who preferred to wait for preconditions to be ready. In the US, the results are completely the opposite, with project managers who preferred making-do experiencing up to 60% less duration delay due to causes of delay that fall mainly into the precondition categories of design and labor availability. By utilizing RF and entropy-based decision tree, this study found that the availability of material, detail design and working method, and labor are the top three preconditions that contribute 20%, 17%, and 4%, respectively, to managers' making-do decisions in China. In the US, the top three preconditions are detail design and working method availability, prerequisite readiness, and management, information flow, or both, which contribute 28%, 10%, and 9%, respectively, to managers' making-do decisions.

This study is useful to project managers and is significant as it outlines and illustrates a method of investigating whether sacrificing starting time pays off with less duration delay, determines the relative importance of delay cause contribution to making-do decision, and identifies the underlying network and associated key trades of a construction project based on spatial proximity. Although this study is based upon comparing surveys in China and the US, the methods presented are repeatable and will enable others to develop a RF approach that is tailored for a specific aspect of a project.

The survey in China was only conducted in one province, whereas the survey in the US was nationwide. However, Shandong province has over 100 million permanent residents, is the second most populous province, and had the third highest gross domestic product (GDP) in China in 2017 (USD 0.15 trillion). Therefore, the survey result is broadly representative of China. Another limitation of this study is the difference in timing of the two surveys. The survey in China was conducted in 2018, whereas the survey in the US was conducted in 2010. However, the findings are still useable and beneficial because although economic conditions and construction technology have changed since 2010, management practice and culture has not changed much, especially for government and public projects performed by civilian contractors. This was confirmed by senior project managers in the interviews for validation. In addition, the survey results were validated by senior project managers in both countries. Therefore, although there could be some differences due to scope and timing, it was still appropriate and valuable to compare how managers perceive delay causes differently in the surveys. The scope of this study is limited to government projects performed by civilian contractors in China and the US. Future research can perform a more in-depth analysis to find out how ready is ready enough from Chinese and US project managers' perspectives. Future findings will be highly valuable in terms of understanding to what extent making-do thresholds are different in different cultures.

Data Availability Statement

Some or all data, models, or code generated or used during the study are available from the corresponding author by request.

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