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A Proactive Risk Assessment Framework to Maximize Schedule Benefits of Modularization in Construction Projects

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Abstract: Various studies developed models and decision support tools to assess the feasibility and optimize the use of modularization. However, none has explored the schedule benefits of modular construction. This paper fills this knowledge gap. To this end, the authors completed the following: (1) analyzed the criticalities of the various modular risk factors on potential schedule savings using data collected from 48 industry professionals, (2) investigated the schedule savings associated with the use of modularization using data collected from 68 modular construction projects, and (3) developed an interrelated assessment model to calculate the schedule savings of using modularization. The provided model was verified using extreme conditions, surprised behavior tests, and sensitivity analysis. Also, it was validated by industry experts. The results show that design and engineering issues, regulatory and organizational matters, and resources and technology aspects are among the top parameters affecting schedule savings of modularized construction projects. This research adds to the body of knowledge by developing a decision-making benchmark that can assist project stakeholders in making proactive decisions, suitable mitigating strategies, and early corrective actions to ensure maximized capitalization on the schedule benefits of modularization in the construction industry. **DOI: 10.1061/(ASCE)CO.1943-7862.0002311.**

Author keywords: Modular construction; Integrated risk assessment; Modular risks.

Introduction

Schedule reduction is considered one of the main drivers behind the adoption of the modular approach in the construction industry (Choi et al. 2019). In addition, a schedule benefit is a key factor in determining the feasibility of the modular approach in construction projects (Murtaza and Fisher 1994). Generally, the schedule benefits associated with the use of modularization in construction projects have been related to various project aspects and attributes. According to Tatum et al. (1987), these schedule benefits are associated with the ability to perform different stages of work synchronously in modular construction as compared to conventional onsite methods, which require all the work to be performed sequentially. Isaac et al. (2016) also highlighted that modularization minimizes the dependencies among the different construction activities and thus reduces the delay effects of one activity on the other. The schedule benefits of modularization are also attributed to improved overall productivity in the project. Such improved productivity is, in turn, associated with reduced weather-related impacts and less exposure to onsite hazards (O'Connor et al. 2015). Other reasons may include reduced delays related to onsite commissioning and testing (Arif and Egbu 2010), decreased workplace congestion (CII 2011), less interference among the various activities (Choi and Song 2014), less rework (Hwang et al. 2018), and minimized onsite plastering, tiling, and scaffolding work in modular projects (Tam and Hao 2014). In addition, the easier incorporation of advanced and modern technologies is perceived to promote further the schedule benefits of modularization in construction projects (Altaf et al. 2018).

Despite the documented schedule advantages, the industry has not been capable of capturing the full benefits of modularization and its potential (Choi et al. 2019). In effect, there are various risks that should be considered when assessing the schedule savings of modularization in the project. For instance, the Kashagan project—a large-scale modular construction project—witnessed various logistics-related risks and challenges, leading to the completion of the project several months later than planned (Carriker and Langar 2014). Another example includes the B2 tower at the Atlantic Yards, which is the tallest residential building constructed using modular construction projects. The project was delayed 20 months due to various unique modular risks, such as tolerance-related issues, extensive rework, and other associated risks (Enshassi et al. 2019). Furthermore, according to a study reported by Koch (2012), offshore modular wind projects witnessed an average schedule overrun of 45% during the 2004–2008 period. Ultimately, the aforementioned project cases emphasize the following statement by Choi et al. (2016) regarding modularization: "The industry continues to struggle with its implementation, and not all executed modular projects have resulted in successful project performance."

Unless construction projects do not meet the minimum feasibility requirements, modular construction methods are generally associated with schedule savings when compared to traditional stick-built methods. However, modularization entails many unique uncertainties

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and sources of risks that should be controlled and mitigated to capture the full schedule benefits of such construction methods (Bertram et al. 2019). According to Rausch et al. (2019), schedule savings of modular construction projects are largely attributed to the proactive management of various associated risks and uncertainties. Therefore, by just considering the differences in labor productivity between onsite and offsite, project stakeholders will not be able to have an adequate benchmark that can help them identify key risks and proactively control their impact on the captured schedule benefits of modularization. Generally, a proactive approach necessitates the need for significant resources and investment during the early project phases (Enshassi et al. 2019).

Many previous approaches have been directed to help practitioners: (1) assess the feasibility of modularization on the one hand (Song et al. 2005; Fisher and Skibniewski 1992; Murtaza and Fisher 1994); and (2) optimize the implementation of modular construction methods on the other (CII 2014; Choi et al. 2016, 2019; Wang and Shi 2013). However, none of the previous studies have proposed an integrated framework that helps industry practitioners explore and assess the impact of modular risks on the realized schedule savings in their construction projects. As such, the goal of this paper is to explore the impact of various project factors on the schedule benefits of modularization on the one hand and, consequently, the development of an assessment benchmark for proactive management and control of modular-related risks on the other.

Related Research Work, Knowledge Gap, and Objectives

The authors reviewed previous research efforts that addressed modularization and its various processes and operations in the construction industry. For instance, Song et al. (2005) developed the Prefabrication, Preassembly Modularization, and Offsite Fabrication (PPMOF) tool that helps industry practitioners identify whether the modular approach is feasible for industrial projects. The decision process takes into consideration the various drivers and barriers to the use of the modular approach in the project. However, the developed model does not help practitioners assess the associated cost and schedule impact (Song et al. 2005). Furthermore, Fisher and Skibniewski (1992) developed a disk operating system called MODEX to determine the feasibility of adopting modularization in a particular construction project. Afterward, software called NEUROMODEX was developed by Murtaza and Fisher (1994) to aid the project team in evaluating the feasibility of modularization in construction projects. Both tools (MODEX and NEUROMODEX) incorporate the same decision factors. However, NEUROMODEX employs a neural network algorithm and can operate with approximate and incomplete inputs. Nevertheless, both tools do not incorporate the capability required to perform quantitative risk-based analysis for the major modularization factors during the decision-making process. Furthermore, Choi et al. (2019) developed a business case model for industrial projects to help practitioners optimize the proportion of working hours to be shifted offsite. The business case model developed by Choi et al. (2019) focused on providing the optimum hours and applying an item-based cost analysis.

Other studies have addressed risks and factors affecting the performance of modular construction projects. For instance, CII (2014) identified critical success factors that promote optimal use of modularization in industrialized projects. Choi et al. (2016) have offered cost and schedule recipes for industrial modular projects. Also, Abdul Nabi and El-adaway (2021) identified the top risk factors affecting the cost and schedule performance of modular construction projects and examined the perception of various stakeholders toward the identified risks. Ultimately, these studies focused only on addressing the key success factors or risk attributes rather than establishing a proactive approach for assessing and maximizing the schedule benefits associated with the use of modularization. On the other hand, Enshassi et al. (2019) proposed a probabilistic risk management framework to address tolerance-based risks in modular construction projects. Furthermore, Enshassi et al. (2020) developed a dynamic and proactive risk-based methodology to address geometric variability problems in modular construction projects. However, the work of Enshassi et al. (2019, 2020) focused only on tolerance and geometric variability risks rather than all the potential risks that might affect modular construction in general and its schedule benefits. In addition, some studies have developed scheduling models for modular construction methods. For instance, Taghaddos et al. (2014) developed a simulation-based multiagent model for the effective allocation of resources in large-scale projects while satisfying project constraints. Lee and Hyun (2019) have proposed a scheduling model for modular construction projects using genetic algorithms. Furthermore, Moghadam et al. (2012) suggested an integrated schedule model comprising BIM and lean principles for a production line of modular construction manufacturing processes. Other examples include the works of Liu and Lu (2019) and Zhang and Flood (2014).

As such, the current literature falls short in exploring the various project aspects and/or factors impacting the schedule savings of modularization on the one hand and establishing a decision-making benchmark for risk control in modular construction projects on the other hand. This paper fills the aforementioned knowledge gap. To this effect, the associated research objectives include the following: (1) analyzing the criticalities of the various modular risk factors on potential schedule savings using data collected from industry professionals, (2) investigating the schedule savings associated with the use of modularization using data collected from modular construction projects, and (3) developing an interrelated assessment model to calculate the potential time impact of using modularization.

Review of Existing Prediction Techniques and Models

The authors reviewed existing models and techniques that have been used in the current literature to predict the schedule performance of construction projects in general. For instance, Jarkas (2016) adopted a linear modeling approach to predict project duration. Ling et al. (2008) utilized multiple linear regression to predict project performance—including schedule—based on various project management practices. Ling et al. (2004) developed a model that predicts schedule performance in design-build and design-bid-build based on 59 variables. Nevertheless, Attallah et al. (2003) utilized statistical regression and the artificial neural network to predict the performance of infrastructure reconstruction projects in terms of different metrics, including project duration. Hong et al. (2011) utilized a simulation model to estimate the schedule performance for core wall construction. Other research studies include the works of the following: (1) Lee et al. (2004), who used discriminant function analysis to develop a model that forecasts project performance based on various management practices, (2) Li et al. (2017), who developed a case-based reasoning model that forecasts schedule for skyscrapers, (3) Mortaji et al. (2015), who proposed a change point analysis as a mean to estimate the duration and cost of projects, and (4) Leon et al. (2018), who

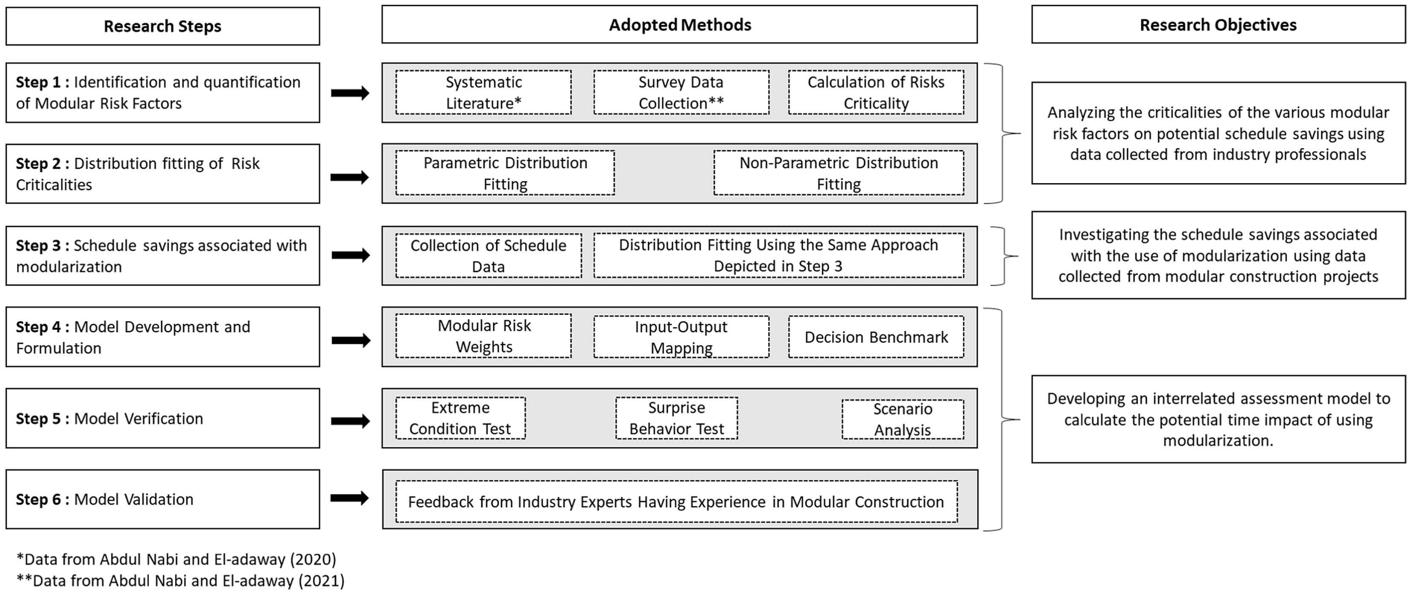

Fig. 1. Adopted methodology. (Data from Abdul Nabi and El-adaway 2020, 2021.)

adopted system dynamics and developed a model to estimate the performance of construction projects.

Ultimately, various techniques have been used to assess the schedule performance of construction projects within different sectors and from different angles, including linear regression, artificial intelligence, and discriminant function analysis, among others. However, the application of these techniques is not optimal for the scope of this paper for two main reasons. The first one is related to the large dataset requirement of these techniques (Nair and Agrawal 2021), which cannot be satisfied given the small modular construction market (Velamati 2012). The second reason is that these techniques do not cover uncertainty and risks nor allow for the establishment of a proactive risk-based approach that can assist in decision-making when assessing project performance. The latter is crucial for the scope of this paper as the maximization of realized schedule savings is highly dependent on proactive managerial decisions and attitudes toward the various modular risks (Rausch et al. 2019). To this end, following a risk-based approach to account for such uncertainties and their impact on the assessment process is crucial to enhance decision-making and proactive risk control in modular construction projects.

The predictive modeling techniques—such as linear regression, earned value management, and artificial intelligence—assess project performance based on previous and/or current project information. However, risk management approaches base their results on project uncertainty and risks to forecast unknown future performance (Babar et al. 2017). Furthermore, risk management can be used for assessing project performance by providing project managers with a benchmark, allowing them to make informed decisions as well as adequate managerial policies and actions (Boyadzhieva-Georgieva 2014). The latter aligns with Baqerin et al. (2016), who emphasized the importance of considering project uncertainties in forecasting project performance and highlighted the following: "In the face of project uncertainties, appropriate forecasting is required to help project decision-makers make informed decisions about the future based on the forecasts." To this end, many previous studies have adopted probabilistic risk-based approaches to forecast project performance. For instance, Assaad et al. (2020) developed a model that predicts schedule and cost overruns in industrial projects by mapping various project risks into probabilistic cost and schedule models. Shahtaheri et al. (2016) developed a stochastic approach to integrating risks and uncertainties of megaprojects in cost and schedule assessment. Keizur and Roberds (2021) examined the evolution of risk-based approaches to estimate the cost and schedule of North American infrastructure projects. Ultimately, the use of an integrated risk approach for assessing project performance has been greatly adopted by previous studies to account for project-related risks and uncertainties. Ultimately, the authors in this study have adopted a risk assessment approach to achieve the goals and objectives of this paper.

Research Methodology

Step 1: Identification and Quantification of Modular Risk Factors

To achieve the goal and objectives of this paper, the authors followed a multi-step research methodology as shown in Fig. 1. Upcoming subsections provide detailed discussion on the reasoning behind the adopted research steps and methods. In order to achieve the goal and objectives of this paper, the authors first need to identify a comprehensive list of modular risks impacting the performance of modularization in construction projects. For this part of the methodology, the authors adopted data collected from previous studies by Abdul Nabi and El-adaway (2020, 2021). The work of Abdul Nabi and El-adaway (2020) identified a comprehensive list of risk factors affecting the performance of modularization in construction projects following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method. The comprehensive list by Abdul Nabi and El-adaway (2020) was established based on systematic literature analysis of published journals addressing the various operations and processes of modular construction methods in the industry. Ultimately, a total of 50 factors were identified and grouped under 8 different categories (Fig. 2), which include the following: cost and profitability, time, quality, safety, environmental, design and engineering, resources and technology, and regulatory and organizational related aspects. For more information related to the identification of modular risk factors, interested readers can refer to the work of Abdul Nabi and El-adaway (2020).

Afterward, Abdul Nabi and El-adaway (2021) developed an online survey to quantify the likelihood of risk occurrence as well

Cost and Profitability

R1. Increased onsite & offsite labor costs
R2. Increased overhead/site preliminary costs
R3. Poor supervision efficiency/costs
R4. Increased Transportation costs
R5. High initial (capital) costs
R6. Increased installation & assembly costs
R7. Increased crane & equipment costs
R8. Increased Design & Engineering costs
R9. Increased cost of materials & modules
R10. Inconsistent cash-flow
R11. Inability to achieve economy of scale

Time

R12. Poor construction Activity Sequencing/Management
R13. Site disruptions & delays
R14. Inclement weather conditions
R15. Long transportation lead times
R16. Increased design & engineering lead times
R17. High shutdown times due to commissioning & testing

Quality

R18. Decreased capacity of quality control
R19. Inefficient quality assurance procedures at the manufacturing plant
R20. Rework
R21. Lack of experienced & capable manufacturers/suppliers
R22. Poor Aesthetics Quality
R23. Geometric variability of modules

Safety

R24. Safety accidents/injuries
R25. High workplace congestion
R26. High exposure to hazards
R27. Poor safety planning & communication

Environmental

R28. Incompliance with environmental standards/ regulations
R29. High material consumption & waste
R30. Low energy efficiency
R31. Incompliance with green practices

Design & Engineering

R32. Low level of standardization
R33. Unanticipated field changes
R34. Late design changes
R35. Unsuitability of design for modularization
R36. Low repetitivity in design
R37. Challenges related to restricted tolerances & interfaces between modules-modules & modules-onsite elements

Resources and Technology

R38. Low onsite/offsite productivity
R39. Inability to incorporate modern technologies
R40. Limited capacity of handling & lifting equipment
R41. Limited capacity of infrastructure & transportation modes
R42. Poor site attributes & logistics
R43. Shortage in stakeholders' experience
R44. Shortage in skilled & experienced labors

Regulatory and Organizational

R45. Lack of adequate collaboration & communication
R46. Cultural resistance towards change & innovation
R47. Contractual risks & disputes
R48. Unsuitability of project delivery method
R49. Legal & Regulatory challenges
R50. Issues related to project permitting

Fig. 2. Modular risk factors. (Data from Abdul Nabi and El-adaway 2020.)

as the schedule and cost impact of each risk. The survey was developed using the Qualtrics system, which is used for online data collection. Construction-related risks are usually assessed by examining two main attributes, which include the likelihood of risk occurrence and relative impact (Shen et al. 2001). To this end, the developed survey consisted of two main sections in which (1) the first included demographic questions; and (2) the second included questions for the evaluation of the likelihood of risk occurrence and relative schedule impacts. It is worth mentioning that Abdul Nabi and El-adaway (2021) adopted the standard 5-point Likert scale established by the Construction Industry Institute (IPRA 2013) for both the likelihood of risk occurrence and relative impacts. Such a unified scale was used to maintain consistency and reduce assessment biasedness by the respondents.

Subsequently, Abdul Nabi and El-adaway (2021) distributed the online survey to 190 industry professionals representing the central stakeholders of a modular construction project (i.e., owners, consultants, contractors, and subcontractors). Ultimately, 48 complete responses (i.e., a response rate of 25.26%) were collected from industry experts experienced in construction in general and modularization. The section "Results and Analysis" provides a detailed discussion on the suitability of the sample size and the respondents' profiles to the scope of this paper.

It is important to note that for the scope of this paper, the authors adopted only the data related to the likelihood of risk occurrence and relative schedule impacts from Abdul Nabi and El-adaway (2021). These data will be used for modeling the risk criticalities as perceived by the modular construction market. Furthermore, the Cronbach's alpha test was conducted to examine the survey validity and internal consistency between the obtained responses under the adopted 5-point Likert scale (Santos 1999). A Cronbach's alpha equivalent to or above 0.75 is considered acceptable, indicating that survey responses are reliable and valid.

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Ultimately, the criticality (C) for each modular risk factor with respect to schedule was calculated using Eq. (1)

$$C_{ri} = L_{ri} \times SI_{ri} \tag{1}$$

where C_{ri} = criticality of risk factor i assessed by respondent r; L_{ri} = likelihood of occurrence for risk factor i assessed by respondent r; and SI_{ri} = schedule impact of risk factor i assessed by respondent r.

Step 2: Distribution Fitting of Risk Criticalities

Generally, risks in the construction industry are assessed by examining two main attributes, including the likelihood of risk occurrence and relative impact (Shen et al. 2001). In effect, traditional risk assessments use these two attributes to quantify the criticality of each risk on construction projects by computing the average likelihood-impact product across all experts or respondents (Marle and Vidal 2016). However, only using the average likelihood-impact product does not reflect the inherent uncertainty and variations in risks from one project to the other. For the scope of this paper, there is a need for a risk assessment approach that provides an assessment benchmark for project stakeholders to assess their project conditions in terms of the impact of the modular risks on the realized schedule savings. Therefore, the overall perception of the modular construction market and variations of risk criticalities from one project to the other should be modeled and considered. To address that, previous studies have quantitatively assessed construction-related risks by modeling the probability distribution of their corresponding criticalities (Li et al. 2016; Assaad et al. 2020). For instance, Li et al. (2016) fitted probability distributions to model and investigate safety-related risks in several Beijing Olympic venue construction projects. Also, Assaad et al. (2020) have fitted probability distribution functions to model the criticality of 25 project risks as perceived by the industrial construction sector. According to Li et al. (2016), probability distributions are advantageous over the traditional approaches as they can reflect the variations of risk criticalities under varying project conditions and situations. Following the same approach, the authors analyzed the modular risks by fitting probability distributions reflecting the perception of the modular market in terms of risk criticality. For each modular risk factor, the authors used the criticalities data C_{ri} computed from Eq. (1) to derive the corresponding distribution functions. In this subsection, the authors discuss the methodology adopted in fitting distribution functions for the modular risk factors. There are two different methods adopted by the authors to fit appropriate distribution functions for the collected data. These methods include the use of *parametric distribution fitting* and *nonparametric distribution fitting*. Subsequent subsections include a detailed discussion on the adopted distribution fitting methods.

Parametric Distribution Fitting

The authors first aimed to fit appropriate distribution functions for the criticalities of modular risk factors using the *parametric distribution fitting* method. In fact, the parametric method assumes that the collected data can be precisely modeled and represented by probability distributions that have a well-defined and known parameter(s), such as normal, Weibull, uniform, extreme value, triangular, inverse Gaussian distribution, and others (Geisser and Johnson 2006). Ultimately, to identify the most suitable theoretical distribution model for the collected data, the authors used the Palisade version 7.5 statistical package. By using such a statistical package, the authors assessed the most appropriate fits for the collected data based on a wide range of possible theoretical distributions (Palisade 2019).

The selection of the best distribution fit requires the use of goodness-of-fit statistics, such as Chi-squared (χ^2), Kolmogorov-Smirnov (KS), Anderson-Darling (AD), Akaike information criterion (AIC), and Bayesian information criterion (BIC) (Haddad and Rahman 2011). Each of the goodness-of-fit tests has its own negative and positive aspects (Laio et al. 2019), and none of them is perceived to outperform the other (Rajsekhar et al. 2015). However, in this paper, the authors adopted χ^2, KS, and AD goodness-of-fit statistics for the selection of the best fit. The reasoning behind the use of these three tests simultaneously is to increase the odds of selecting the distribution that satisfies the properties of the collected data, such as the skewness of the data and the tails. The evaluation is conducted using the most widely adopted confidence interval, which is 95% (Peng et al. 2020). Thus, the results of the three tests are evaluated at a significance level of 0.05. The distribution fit that satisfies most of the goodness-of-fit test statistics is selected. In case there are multiple potential fits, the authors select the best fit based on AIC, which is a method that has an information entropy and reflects the lost information associated with the adopted distribution models (Rajsekhar et al. 2015). Therefore, the best candidate is chosen based on the lowest AIC values—that is, the one that is associated with the lowest information loss. If none of the applicable theoretical distributions results in a p-value greater than 0.05 for any of the three conducted statistical tests, the *nonparametric distribution fitting* method is used by the authors.

Upon selecting the best parametric distribution model, the authors shall ensure proper boundary conditions. For instance, the probability distribution functions should not be defined for numbers above 25 or below 1. Therefore, truncation is conducted so that the adopted distribution models fit adequately to the corresponding data range of the modular risk factors, which is (1, 25). Therefore, all the fitted distribution functions found to be defined over values outside their respective data ranges are truncated using Eq. (2)

$$T(C) = \frac{\int_a^C f(C)dC}{\int_a^b f(C)dC} \tag{2}$$

where $T(C)$ = truncated cumulative distribution function of a modular risk factor over the interval [a, b]; $f(C)$ = fitted parametric probability distribution before truncation; a = minimum boundary value for the distribution, which is 1 for the modular risk factors; and b = maximum boundary value for the distribution, which is 25 for the modular risk factors.

Nonparametric Distribution Fitting

The authors utilized the *nonparametric distribution fitting* method whenever the authors were not able to find a theoretical distribution fit that satisfied at least one of the three conducted goodness-of-fit tests. Nonparametric/empirical distributions refer to manually fitted functions that do not possess predefined parameters (Vose 1996). In fact, polynomial functions are the most convenient techniques used for fitting empirical distributions due to their simplicity, ease of use, and well-known properties (NIST/SEMATECH 2018). Furthermore, polynomial models provide the ability and required flexibility to represent complex functions and data with various structures (NIST/SEMATECH 2018). Therefore, the authors utilized polynomial functions for fitting nonparametric distribution functions while preserving the general properties of a continuous distribution function. The general properties of a continuous distribution function include the following: (1) nonnegativity property over the whole data range, (2) unity property (i.e., the functions integrated into one), and (3) continuity property (Assaad et al. 2020).

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Nonnegativity Property. The authors first tried to fit one polynomial function that satisfies the nonnegativity property over the entire data range. Because no single polynomial function adequately represented the whole data and satisfied the nonnegativity property, the authors utilized the method adopted by Assaad et al. (2020), in which data were split into ranges and then fitted using multiple polynomial functions. Thus, the authors divided the data into two ranges or intervals in which each range was fitted and modeled by one polynomial function. The polynomial function for the first range of the data is denoted as $f_1(C)$ and that for the second range as $f_2(C)$. Because two polynomial functions are being fitted, there should be a split point denoted as α separating the data into two ranges such that $f_1(\alpha) = f_2(\alpha)$. In case no two polynomial functions adequately represented the data and satisfied the nonnegativity property, the authors had to divide the data into three ranges further. Similarly, each part is modeled and fitted by one polynomial function in which that of the first part is denoted as $f_1(C)$, that of the second part as $f_2(C)$, and that of the third part as $f_3(C)$. In this case, there should be two split points to separate the data into three ranges denoted as α and β, respectively. Similarly, the split points should satisfy $f_1(\alpha) = f_2(\alpha)$ and $f_2(\beta) = f_3(\beta)$. Ultimately, the nonnegativity property was maintained by fitting only positive polynomial functions over the entire range of the data.

Unity Property. Another property that the fitted polynomial functions should satisfy is the unity property. In other words, and for the modular risk factors fitted using two polynomial functions, the authors derived the cumulative distribution functions by ensuring that the summation of the first and second polynomial functions integrates into 1. Therefore, the first polynomial function was truncated as to be strictly defined over [1, α] and the second polynomial function over [α, 25]. In the case of fitting three polynomial functions, the authors truncated the first polynomial function over [1, α], the second polynomial function over [α, β], and the third polynomial function over [β, 25].

Continuity Property. The last property that should be satisfied is the continuity property. For this paper, cumulative distribution functions are more relevant to the developed model. Therefore, the cumulative fitted distribution functions are derived directly by integrating the probability density function. In the case of fitting the data using two polynomial functions, the continuity property is preserved by ensuring that $F_1(\alpha) = F_2(\alpha)$. To do so, the first polynomial should integrate up to the actual value of $F_1(\alpha)$—which is obtained from the empirical distribution of the data—and it is denoted as γ. As for the second polynomial function, its integration boundaries should range from γ up to 1. Ultimately, Eqs. (3) and (4) represent the truncated distribution function of the data satisfying the nonnegativity, continuity, and unity properties

$$F_1(C) = \frac{\int_1^C f_1(C)dC}{\int_1^\alpha f_1(C)dC} \times \gamma \quad \text{over the first interval } [1, \alpha] \tag{3}$$

$$F_2(C) = \frac{\int_\alpha^C f_2(C)dC}{\int_\alpha^{25} f_2(C)dC} \times (1-\gamma) + \gamma \quad \text{over the second interval } [\alpha, 25] \tag{4}$$

where α = point splitting the entire data [1, 25] into two ranges [1, α] and [α, 25]; $f_1(C)$ = fitted polynomial function for the first range $[1, \alpha]$; $F_1(C)$ = derived cumulative distribution function for the first range of data $[1, \alpha]$; $f_2(C)$ = fitted polynomial function for the second range of data $[\alpha, 25]$; $F_2(C)$ = derived cumulative function of the second part $[\alpha, 25]$; and γ = value of the empirical function of the data at the split point α.

On the other hand, and in the case of fitting the data using three polynomial functions, the continuity property of the derived cumulative distribution functions should be preserved by ensuring that the split points α and β satisfy $F_1(\alpha) = F_2(\alpha)$ and $F_2(\beta) = F_3(\beta)$, respectively. The values of the empirical distribution of the data at α and β are used while deriving the cumulative distribution function, and they are denoted as γ and φ, respectively. The truncated cumulative distribution function is then derived using Eqs. (5)–(7)

$$F_1(C) = \frac{\int_1^C f_1(C)dC}{\int_1^\alpha f_1(C)dC} \times \gamma \quad \text{over the first interval } [1, \alpha] \tag{5}$$

$$F_2(C) = \frac{\int_\alpha^C f_2(C)dC}{\int_\alpha^\beta f_2(C)dC} \times (\varphi - \gamma) + \gamma \quad \text{over the second interval } [\alpha, \beta] \tag{6}$$

$$F_3(C) = \frac{\int_\beta^C f_3(C)dC}{\int_\beta^{25} f_3(C)dC} \times (1 - \varphi) + \varphi \quad \text{over the third interval } [\beta, 25] \tag{7}$$

where α and β = split points dividing the entire data [1, 25] into three ranges, [1, α], [β, α], and [β, 25]; $f_1(C)$, $f_2(C)$, and $f_3(C)$ = fitted polynomial functions for the first range of data [1, α], second range $[\beta, \alpha]$, and third range [β, 25], respectively; $F_1(C)$, $F_2(C)$, and $F_3(C)$ = fitted cumulative distribution functions of the first range $[1, \alpha]$, second range $[\beta, \alpha]$, and third range [β, 25], respectively; and γ and φ = values of the empirical distribution function of the data at the split points α and β, respectively.

Step 3: Schedule Savings Associated with Modularization

According to Baqerin et al. (2016), "Faced with project uncertainties, researchers and practitioners often use statistical distributions to provide subjective estimates and fit curves to observed data." In fact, many previous researchers have followed such an approach to address the impact of uncertainties and risks on various project outcomes, such as the following: (1) AbouRizk and Halpin (1992), who fitted probability distributions to construction duration data, (2) Tam et al. (2008), who utilized Gaussian and hyperbolic distributions for quality management and improvement in construction projects, and (3) Baqerin et al. (2016), who examined the applicability of the Weibull distribution to evaluate the schedule performance of repetitive projects. Following the same approach, the authors need to establish a statistical distribution to model the potential schedule savings that may be incurred using the modular construction approach in construction projects under varying conditions and situations.

Based on that, there is a need to collect data from real construction projects. It is important to highlight that the scope of this paper is to estimate the schedule benefits associated with the adoption of modularization in construction projects rather than the schedule performance with respect to the baseline or planned schedule. Unless construction projects do not meet the minimum feasibility requirements, modular construction methods are generally associated with schedule savings when compared to traditional stick-built methods. To this end, for this paper, the collected data included the schedule savings incurred by the adoption of the modular approach in the construction project. Ultimately, the collection of schedule savings data was conducted in a percentage format based on 68 real construction projects delivered using modular construction methods. The schedule data was collected to reflect the captured savings estimated after the execution of the modular construction

projects and as compared to similar traditional stick-built construction projects. Modeling the probability distribution of schedule savings captured by the industry due to the use of modularization on the one hand and risk criticalities on the other does not necessitate any interconnectivity between both data during the collection process. Therefore, like several previous studies (Assaad et al. 2020), data mismatching is acceptable and does not alter the validity of the adopted methods and obtained results. Therefore, the collection process was conducted by distributing a separate short online survey and referring to publicly available case studies. The survey questions are related to the project characteristics and description, corresponding sector, and estimated captured schedule savings associated with the use of modular construction in the project. Ultimately, using the collected data, the authors were able to fit a distribution function and model the schedule savings associated with the use of the modular method in the construction industry. The authors adopted the same methodology depicted in the previous subsection, "Distribution Fitting of Risk Criticalities."

Step 4: Model Development and Formulation

Whenever a risk has increased criticality on a given project, the likelihood of its impact is perceived to increase. This also applies to the scope of this paper, in which any increase in the criticality of a modular risk would increase the likelihood of its impact on—or decreased percentage value of—the realized schedule savings in the project. To account for that, the relationship or mapping process between the input (criticalities of modular risks) and output (schedule savings) should be formulated by considering the percentile level corresponding to the risk criticalities on a given project. The percentile level has been widely used for similar purposes to model uncertainties and map their impacts on various construction and engineering management outcomes (Sakka and El-sayegh 2007; Assaad et al. 2020; Isidore and Back 2001). Following the same approach, the authors mapped the percentile level associated with each risk criticality into the fitted distribution functions of schedule savings data. Such mapping assumes that a high percentile level of a modular risk (i.e., high associated schedule criticality) should increase the percentile level of schedule savings (i.e., decrease the realized schedule savings) associated with the project.

However, each modular risk has a different degree of impact on the realized schedule savings. To this end, there is a need to account for the contribution or importance of each risk factor toward the schedule performance of modular construction methods. To this end, relative weights were calculated in this paper using the weighted average method to quantify the contribution of each modular risk factor toward the schedule performance of modular construction methods. The relative weights for the individual modular risk factors are calculated based on the average criticality values obtained from the survey responses and using Eq. (8)

$$w_i = \frac{\overline{C_i}}{\sum_{i=1}^{i=50} \overline{C_i}} \tag{8}$$

where w_i = computed relative weight of a modular risk i; and $\overline{C_i}$ = average criticality of a modular risk i obtained from the survey responses.

Based on the discussion beforehand, the assessment of schedule savings on any construction project is formulated as follows:

- the assessment of the likelihood of risk occurrence and relative schedule impact for each modular risk factor using the IRPA (2013) scale and based on the conditions of and/or managerial policies adopted in the project;
- calculation of the criticality of each modular risk factor by using Eq. (1). In case the assessment is conducted by multiple project team members, the average criticality across all members is considered as the input for the model;
- based on the computed criticalities, the percentile level $F_i(C)$ to each modular risk factor is determined using the distribution functions obtained from the section "Distribution Fitting of Risk Criticalities";
- a weighted percentile level $\overline{F}$ computed by multiplying the $F_i(C)$ values with their corresponding relative weights obtained from Eq. (8). The weighted percentile level $\overline{F}$ is computed as shown in Eq. (9)

$$\overline{F} = \sum_{i=1}^{50} w_i \times F_i(C) \tag{9}$$

  where w_i = relative weight of a modular risk i; $F_i(C)$ = percentile level for a risk factor i assessed at a value C specified by the project team; and $\overline{F}$ = weighted average level of percentile of all evaluated modular risks; and
- based on $\overline{F}$, the schedule benefits (S) associated with the use of modularization in the project retrieved by setting $F(S) = \overline{F}$, where $F(S)$ is the fitted cumulative distribution function for the schedule performance data obtained in the subsection "Schedule Savings Associated with Modularization" of the methodology.

To further enhance the benefits of the developed model, the authors established a benchmark that can assist practitioners in the assessment and decision-making process. Such a benchmark should help project stakeholders determine whether there are possibilities to further enhance capitalization on the schedule benefits of modularization. To this end, the benchmark was obtained by following the previously depicted five steps to assess the schedule savings associated with the average responses (i.e., average likelihood and impact) received from the industry experts. Ultimately, the assessed schedule savings is used in the developed model as a benchmark during the decision-making and assessment process. For illustrative purposes, the authors further provided two case scenarios to reflect how the model can be used on construction projects along with the developed benchmark during the decision-making process. The "Results and Analysis" section provides detailed information on the developed model and established benchmark.

Step 5: Model Verification

Any model should be verified to check if researchers created the model appropriately (Uslu et al. 2013). In fact, model verification is crucial to assess whether the developed model behaves like the real system (Nasir and Hadikusumo 2019). To this end, the authors verified the developed research steps by conducting the following: (1) the extreme condition tests to examine whether a developed model is robust when dealing with extreme inputs; and (2) surprise behavior tests to examine whether the behavior of the model deviates from that of the real system (Nasir and Hadikusumo 2019). For the extreme condition test, the authors examined the behavior of the developed model in the case of extreme criticality values for the modular risk factors (i.e., 1 and 25). As for the surprise behavior test, the authors examined if the absolute schedule savings values obtained from the model increases as the criticality values of the modular risk factors decrease and vice versa. In addition to the aforementioned verification tests, the authors performed a sensitivity analysis to identify the top influential modular risk categories and factors. A sensitivity chart was developed to identify the modular risk categories that are more influential on the schedule savings

associated with the use of the modular approach in construction projects. More details on the developed sensitivity analysis are present in the "Results and Analysis" section.

Step 6: Model Validation

Model validation determines the degree to which a developed system or model fulfilled the needs of the end-users (Gupta 1991). To this end, the authors validated the developed model by referring to experts experienced in the construction industry and modular construction methods. The validation process is comprised of two steps in which (1) the experts first test the model on actual ongoing projects, and (2) the experts then provide qualitative feedback related to the benefits, value, and comprehensiveness of the developed model. A qualitative validation process was adopted as the model is developed based on a risk assessment approach that is mainly used for risk control rather than for precise quantitative assessment. Nevertheless, many previous construction and engineering management-related studies have proposed decision-making and risk assessment models and validated them using a qualitative approach, such as the works by (1) Abotaleb et al. (2020), who developed a risk rating score system to evaluate the level of project susceptibility to out-of-sequence work and qualitatively validated it using the feedback of industry experts; and (2) Hu et al. (2016), who developed a program organization performance index and validated it using qualitative feedback from five industry experts. Ultimately, a qualitative validation was performed by sharing the developed model with five leading contracting companies in the national modular construction market, in which a total of 25 experts participated in the validation process. The cumulative industry experience of these companies sums up to 352 years with a total of 6,500 employees and \$12.25 billion cumulative annual revenue. To this end, these companies are of high value in validating the model in terms of its comprehensiveness, practicality, and benefits. Ultimately, the experts were provided with the tool in an automated Microsoft Excel version 2019 file format to implement it and consequently give feedback. It is important to note that the experts were also provided with a user guide depicting instructions on how to implement the developed tool. The validation process was iterated and performed in several rounds. In each round, the experts implemented the tool and consequently wrote feedback in a bullet format. After receiving feedback, the authors conducted changes and adjustments based on experts' recommendations and sent back the tool for another round. The process was repeated until no further adjustments or recommendations were provided by the industry panel. In the end, a total of three rounds were performed with a 100% participation rate in each round. The results of an actual case study project, along with the summary of the experts' feedback, are provided in the "Results and Analysis" section.

Results and Analysis

Survey Validity and Sample Characteristics

The accuracy of the developed model is highly dependent on avoiding biases and subjectivity in the data collected from the targeted sample. To this end, the authors examined the survey validity on the one hand and the representativeness of the collected survey data on the other. For the survey validity, the authors performed Cronbach's alpha test, and the obtained coefficients were 0.947 and 0.959 for the likelihood of occurrence and the impact on schedule, respectively. Because both coefficients were found to be higher than 0.75, it could be concluded that the developed survey was reliable and valid. As for the sample sufficiency, it was examined through a statistical technique developed by Cochran (1977) and used in many related research studies. The statistical technique computes the minimum required sample size to ensure the sufficiency of the collected data, as shown in Eq. (10)

$$n = \frac{(t^2)(s^2)}{(e^2)} \tag{10}$$

where n = minimum number of responses; $t = Z$ -statistic of the selected significant value (α); s = estimate of variance deviation concerning the utilized scale, which is obtained by dividing the range of the scale over the number of standard deviations for nearly all potential values of such a range; and e = scale points (5) multiplied by the satisfactory margin of error.

A significance level of 95% was used for this test, where α is 0.05 (Kamali and Hewage 2017). The t value, associated with a significance level of 95%, is 1.96 (Kamali and Hewage 2017). As for the s value, Cochran (1977) highlighted four different ways to estimate the variance of the sample size, including the use of previous studies targeting similar populations. According to Bartlett et al. (2001), such a method is considered logical, and it is expected to produce valid estimates of the variance. For a 5-point Likert scale, previous studies targeting populations experienced in the construction industry used a sample variance of either $5/6$ or $5/4$ (Assaad et al. 2020; Fellows and Liu 2015; Hatamleh et al. 2018). To be more conservative, and as recommended by Bartlett et al. (2001), the authors used a value of s equal to $5/4$. As for the accepted margin of error, a value of 10% was assumed based on its common use in various construction-related studies (Heravi and Jafari 2014; Idowu and Lam 2020). Therefore, the e value becomes equal to (5×0.1). To this end, the value of n is found to be equal to $24.01 \approx 25$. By fixing all assumed values of the confidence interval ($t = 1.96$) and sample variance ($s = 5/4$), Eq. (10) shows that a sample size of 48 is associated with a margin of error equal to approximately 7%, which is considered acceptable. Therefore, the sample size is considered sufficient to ensure valid generalization.

To further check the sufficiency of the sample size, an empirical examination is also presented by comparing the obtained response rates with previous studies related to construction and engineering management fields, including studies by the following: (1) Assaad et al. (2020), who considered that a response rate between 20% and 30% was acceptable for survey-based research related to construction field, (2) Fellows and Liu (2015), who indicated an acceptable range between 25% and 35% in construction, and (3) Tan et al. (2014), who considered an acceptable response rate to be between 10% and 20%. Therefore, having a sample size of 48 respondents for a 25.62% response rate is acceptable when compared with previous construction and engineering research work employing surveys for data collection. It is important to note that such a low response rate is expected as the construction industry is known to have a low rate of participation in surveys (Wu et al. 2015). Furthermore, Manfreda et al. (2008) highlighted that online-based surveys are more likely to have lower response rates. According to Fellows and Liu (2015), low response rates in construction research are triggered by the highly labor-intensive nature of survey techniques on the part of the respondents and the researcher.

As for the respondents' profiles, the 48 respondents reflect an average experience of 24.25 years in the construction industry and 13.6 years in modular construction methods. Furthermore, the respondents reflect the perception and evaluation of various stakeholders' groups (i.e., owners, contractors, consultants, and subcontractors), as shown in Fig. 3. The career levels of the overall respondents

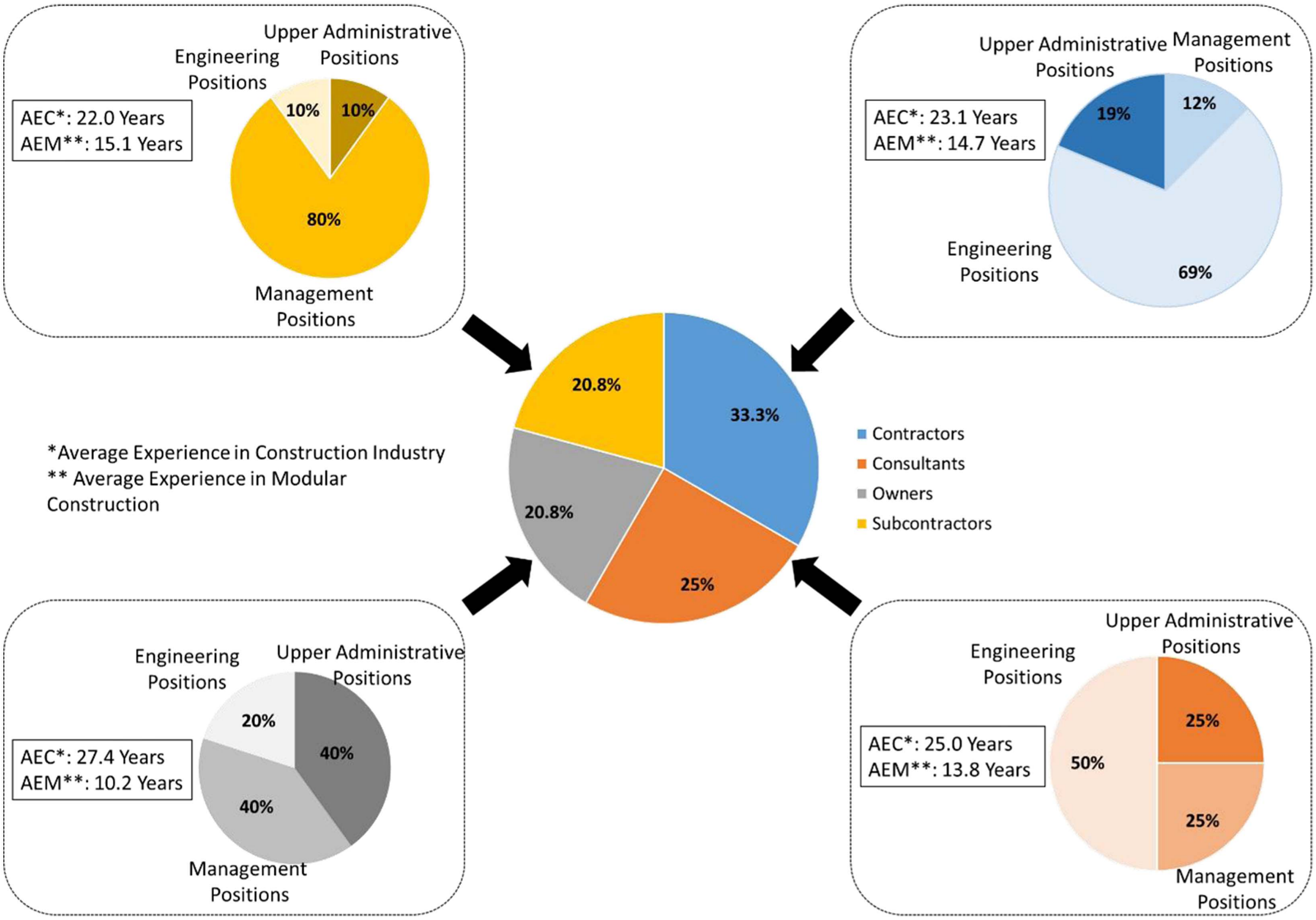

Fig. 3. Demographic distribution of survey respondents.

comprised 20.84% upper administrative positions (i.e., chief executive officers, program directors, and vice presidents), 54.16% management positions (i.e., construction, area/regional, operation, and project managers), and 25% engineering positions (architects, designers, site/field, estimation, and planning engineers). Fig. 3 shows the career level, average experience in construction, and modularization of the respondents within each stakeholder group.

As shown in Fig. 3, the respondents within each stakeholder group possess an average experience in construction greater than or equal to 22 years and an average experience in modular construction greater than 10 years. Furthermore, most of the respondents (i.e., more than 75%) possessed high managerial and administrative positions in the construction industry. Nevertheless, the authors further compared the average experience of the respondents in this paper with previous construction-related studies, such as the work of Choi et al. (2020), who identified the various technologies needed to enhance the level of standardization in design and modularization based on survey data collected from respondents with an average experience of 21.75 years. Other examples include the works by Rahman (2014), who noted an average of 23 years of experience, Patel and Jah (2016), who noted an average of 11.4 years, and Kakar et al. (2020), who noted an average of 13 years. Ultimately, the responses are good representatives of the construction industry in general and modular construction in terms of the sufficiency of the sample size and the appropriateness of the respondents' profiles for the analysis of this paper.

Fitted Distributions for Modular Risk Factors

The authors derived cumulative distribution functions for the risk factors to reflect the uncertainties and variations from one project to the other as related to their criticalities with respect to the schedule savings. The authors first aimed to fit theoretical distribution functions. Ultimately, 46 modular risk factors were fitted using theoretical distribution functions, such as uniform, triangular, and extreme values, among others. After selecting the best fit for the 46 modular risk factors, the distribution functions were truncated and subsequently derived using Eq. (2). As for the other four risk factors, their distributions were fitted using the nonparametric method. These four modular risks include R29: high material consumption and waste; R30: low energy efficiency; R31: incompliance with green practices; and R34: late design changes. These risk factors' data were fitted by using either two or three polynomial functions while preserving the three general properties of distribution functions. Therefore, the cumulative distribution functions for modular risks fitted using two polynomial functions (i.e., R30, R31, and R34) were derived from Eqs. (3) and (4). On the other hand, R29 was fitted using three polynomial functions, and thus, its cumulative distribution function was derived from Eqs. (5)–(7). The derived cumulative distribution functions for the criticalities of each modular risk factor are plotted and then presented in Figs. 4 and 5. Furthermore, the figures present the industry criticality average (i.e., average criticality across the 48 respondents) as a vertical dotted line.

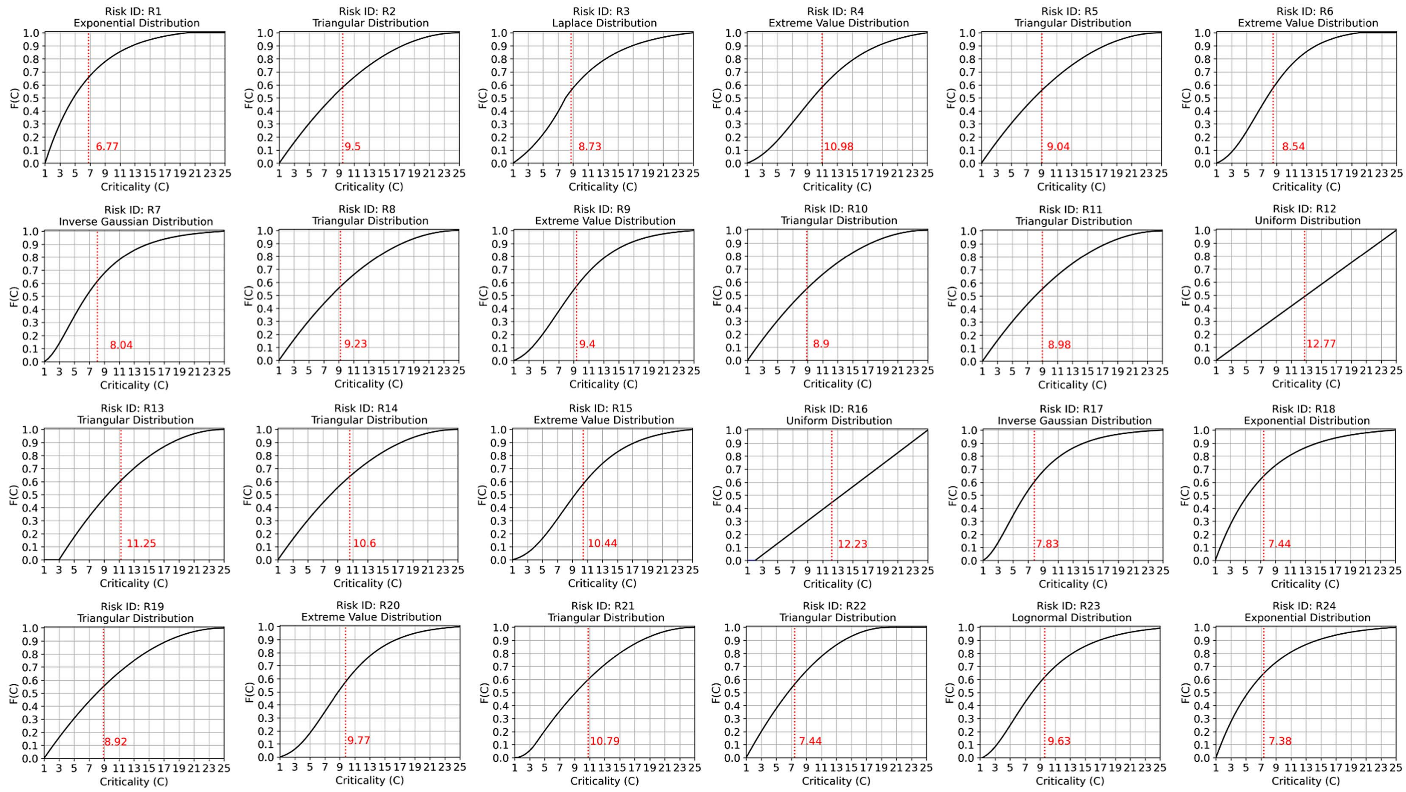

Fig. 4. Fitted cumulative distribution functions for the modular risks.

According to Assaad et al. (2020), project risks fitted using nonparametric methods mainly have similar characteristics in terms of their complex nature, ability to quantify their impacts only after their occurrence, and inability to predict their occurrence instantly. As shown in Figs. 4 and 5, the project risks fitted using nonparametric methods have many curvatures indicating their complex nature and impact on schedule savings of modular construction methods. Ultimately, industry practitioners are advised to take early measures to alleviate the occurrence of such risks and so avoid their complex impact on the schedule benefits of modularization on construction projects.

Schedule Savings Associated with Modularization

The authors collected schedule savings associated with the use of modularization from 68 real construction projects. The targeted projects pertain mainly to the US building and commercial sectors, including office buildings, laboratories, hotels, banks, retail buildings, and others. Furthermore, all the selected projects employed volumetric types of modular methods (i.e., constructing three-dimensional modules offsite and delivering them to the site for installation). The collected schedule savings ranges from 1% to 85%. These construction projects reflect an average schedule savings of 34% associated with the use of modular construction methods. The collected data shows that all schedule data indicates schedule savings when adopting modular methods in construction projects. The latter is expected as various previous research works highlighted schedule reduction as the main driver in adopting modular methods on construction projects (Isaac et al. 2016; O'Connor et al. 2015; Tatum et al. 1987).

Upon collecting the data, the authors aimed to fit theoretical distribution functions following the *parametric distribution fitting* method. The results of the three conducted goodness-of-fit tests showed no consensus on a single theoretical distribution. Therefore, the authors selected the best distribution based on the lowest AIC value. To this end, the best fit for the schedule savings data is the normal distribution, which is defined by two parameters: the location parameter μ and the squared scale parameter σ^2. The fitted normal distribution for the schedule savings possesses a location parameter of -0.34074 and a squared scale parameter of 0.19940. The truncated normal cumulative distribution is then derived using Eq. (2) and subsequently plotted in Fig. 6. It is worth noting that all the collected data are negative as they represent schedule savings only rather than schedule savings and growths. The latter aligns with the objective of this paper, which is strictly maximizing and assessing the schedule savings of modularization in construction projects. Therefore, the developed model is used only when modularization is perceived to be feasible for the project at hand.

Established Assessment Model

In order to formulate the assessment model, there is a need first to quantify the contribution and importance of each modular risk toward the realized schedule savings associated with the use of modular construction methods. To this end, the weight of each modular risk was calculated based on Eq. (3) and by using the industry average shown in the second column of Table 1. Ultimately, the calculated weights were calculated and then presented in the third column of Table 1. Industry practitioners are recommended to adopt the weights presented in the table while assessing the schedule savings associated with the use of the modular approach in their construction projects. However, if enough information is available to quantify the contribution of each modular risk with respect to the schedule savings, industry practitioners can use different weights than the ones provided in this paper. In this case, the sum of the weights allocated by the users should add up to 100%.

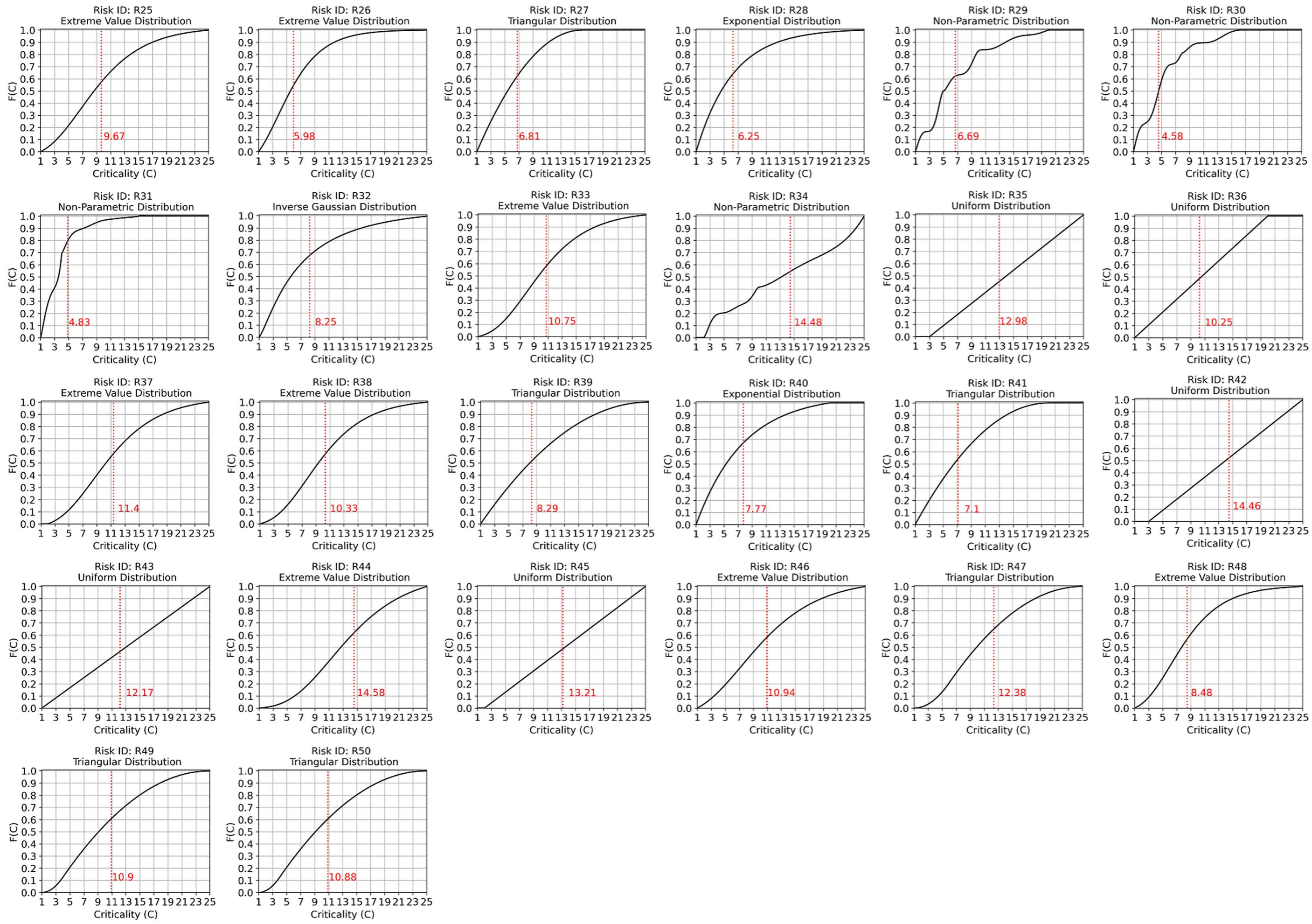

Fig. 5. Fitted cumulative distribution functions for the modular risks (continued).

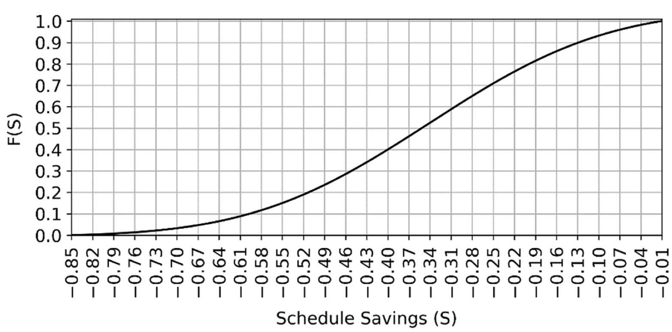

Fig. 6. Graph of the truncated cumulative distribution function for schedule savings.

Upon calculating the weights, the authors formulated the model as depicted in the equations of the subsection "Model Development and Formulation" of the methodology to develop the risk assessment model. Furthermore, the authors established a decision-making benchmark based on the industry average of risk criticalities shown in the second column of Table 1. To do so, the graphs of Figs. 4 and 5 were used to obtain the percentile level $F_i(C)$ for each modular risk based on its corresponding industry criticality average. The percentile levels $F_i(C)$ for all the modular risk factors are shown in the third column of Table 2. Then, the weighted percentile level $\overline{F}$ was calculated using Eq. (9) by multiplying each percentile level with its corresponding weight. The computed $\overline{F}$ is then utilized to map the associated schedule savings by setting the weighted percentile level $\overline{F}$ equal to $F(S)$ and subsequently finding the corresponding savings using Fig. 6. Ultimately, the established decision-making benchmark is equal to 31.70% (Fig. 7), representing the schedule savings estimated assuming all modular risks have risk criticalities equal to the industry average.

To illustrate how the established decision-making benchmark can help practitioners in the assessment process on any construction project, the authors presented two case scenarios: (1) Case A assumes all the criticalities of risk factors are equal to 5; and (2) Case B assumes all the criticalities of risk factors are equal to 15. Ultimately, the authors used the graphs of Figs. 4 and 5 to find the $F_i(C)$ for each modular risk and then calculated $\overline{F}$ using Eq. (9). The percentile levels of each modular risk factor and weighted percentile levels for Case A and Case B are shown in the fourth and fifth columns of Table 1, respectively. The estimated schedule savings for Case A were found to be equal to 47.78%, which is greater than 31.70% (Fig. 7). The latter indicates that the project conditions are associated with schedule savings higher than the industry average, and thus, the schedule benefits are efficiently captured in the project. As for Case B, the estimated schedule savings are equal to 20.48% (i.e., less than 31.70%), indicating that schedule benefits in the project may not be fully realized, and so mitigating strategies and corrective actions should be considered.

Table 1. Calculated weights, decision-making benchmark, and case scenarios

Risks	Industry average (1–25)	Weights (%)	Corresponding percentile level $F_i(C)$ (0 1)		
			Benchmark[a]	Case A[b]	Case B[c]
R1	6.77	1.41	0.66	0.52	0.95
R2	9.50	1.98	0.58	0.31	0.83
R3	8.73	1.82	0.56	0.22	0.85
R4	10.98	2.29	0.58	0.17	0.79
R5	9.04	1.89	0.56	0.31	0.83
R6	8.54	1.783	0.579	0.244	0.922
R7	8.04	1.679	0.615	0.349	0.905
R8	9.23	1.927	0.568	0.306	0.826
R9	9.40	1.962	0.573	0.213	0.864
R10	8.98	1.857	0.550	0.306	0.826
R11	8.90	1.875	0.554	0.306	0.826
R12	12.77	2.666	0.490	0.167	0.583
R13	11.25	2.349	0.609	0.174	0.793
R14	10.60	2.214	0.640	0.306	0.826
R15	10.44	2.179	0.582	0.162	0.828
R16	12.23	2.553	0.445	0.130	0.565
R17	7.83	1.635	0.605	0.347	0.913
R18	7.44	1.553	0.648	0.474	0.908
R19	8.92	1.862	0.551	0.306	0.826
R20	9.77	2.040	0.577	0.184	0.856
R21	10.79	2.253	0.599	0.206	0.802
R22	7.44	1.553	0.563	0.377	0.931
R23	9.63	2.009	0.620	0.248	0.855
R24	7.38	1.540	0.647	0.477	0.910
R25	9.67	2.018	0.573	0.216	0.844
R26	5.98	1.248	0.546	0.441	0.961
R27	6.81	1.422	0.625	0.462	0.996
R28	6.25	1.305	0.639	0.539	0.940
R29	6.69	1.396	0.621	0.502	0.853
R30	4.58	0.957	0.496	0.585	0.988
R31	4.83	1.009	0.791	0.809	0.999
R32	8.25	1.722	0.674	0.455	0.887
R33	10.75	2.244	0.580	0.148	0.813
R34	14.48	3.023	0.547	0.206	0.564
R35	12.98	2.710	0.454	0.091	0.545
R36	10.25	2.140	0.487	0.211	0.737
R37	11.40	2.379	0.579	0.116	0.781
R38	10.33	2.157	0.573	0.159	0.828
R39	8.29	1.731	0.515	0.306	0.826
R40	7.77	1.622	0.673	0.475	0.930
R41	7.10	1.483	0.539	0.377	0.931
R42	14.46	3.019	0.521	0.091	0.545
R43	12.17	2.540	0.465	0.167	0.583
R44	14.58	3.045	0.619	0.060	0.644
R45	13.21	2.758	0.487	0.130	0.565
R46	10.94	2.284	0.581	0.192	0.782
R47	12.38	2.584	0.650	0.133	0.781
R48	8.48	1.770	0.567	0.249	0.902
R49	10.88	2.275	0.605	0.206	0.802
R50	10.90	2.270	0.604	0.206	0.802
Weighted percentile level $\overline{F} = F(S)$			0.573	0.254	0.790

[a]The criticality of modular risks equals the industry averages.
[b]The criticalities of all modular risks are equal to 5.
[c]The criticalities of all modular risks are equal to 15.

Table 2. Results of the project case study

Risks	Step 1–2: risk assessment	Step 3: corresponding percentile level $F_i(C)$ (0 1)
R1	6.77	0.66
R2	9.50	0.58
R3	8.73	0.56
R4	14.70	0.78
R5	12.40	0.72
R6	8.54	0.58
R7	8.04	0.62
R8	14.40	0.80
R9	9.40	0.57
R10	8.90	0.55
R11	11.84	0.70
R12	11.49	0.44
R13	11.25	0.61
R14	10.60	0.64
R15	10.44	0.58
R16	14.24	0.53
R17	7.83	0.61
R18	7.44	0.65
R19	8.92	0.55
R20	9.77	0.58
R21	10.79	0.60
R22	7.44	0.56
R23	3.48	0.12
R24	7.38	0.65
R25	16.15	0.88
R26	5.98	0.55
R27	6.81	0.62
R28	6.25	0.64
R29	6.69	0.62
R30	4.58	0.50
R31	4.83	0.79
R32	8.25	0.67
R33	10.75	0.58
R34	20.00	0.71
R35	7.58	0.21
R36	10.25	0.49
R37	11.40	0.58
R38	10.33	0.57
R39	8.29	0.52
R40	7.77	0.67
R41	7.10	0.54
R42	14.46	0.52
R43	12.17	0.47
R44	14.58	0.62
R45	13.21	0.49
R46	10.94	0.58
R47	12.38	0.65
R48	8.48	0.57
R49	10.90	0.61
R50	10.88	0.60
Step 4: weighted percentile level $\bar{F} = F(S)$		0.583
Step 5: estimated schedule savings		31.22%

In general, if the schedule savings estimated for the project are less than that of the average industry schedule savings, the project team should be informed that current project conditions do not favor an optimal capitalization on schedule benefits of modularization, and consequently, appropriate mitigating strategies and corrective actions should be considered. Ultimately, the computed schedule savings of 31.70% can be used in the model as a benchmark to decide whether there is a chance for further maximization of schedule benefits of modular construction in the project. Even if the estimated schedule savings are found to be higher than 31.70%, the project team can further use the developed model for risk control in the project.

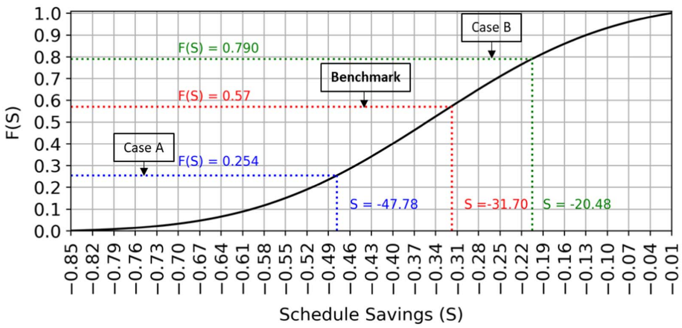

Fig. 7. Decision-making benchmark and schedule savings of Case scenarios A and B.

Model Verification

Extreme Condition and Surprise Behavior Tests

The first extreme condition includes having all the criticality values of the modular risk factors equal to 1. In this case, the $F_i(C)$ have zero values, as reflected in the graphs of Figs. 4 and 5. By multiplying each $F_i(C)$ by its corresponding weight w_i presented in Table 2, the value of $\overline{F}$ computed using Eq. (9) becomes equal to zero. Therefore, and by setting $\overline{F} = F(S)$, the graph in Fig. 6 reflects a value of S equal to -0.85, which is the minimum value S can take in the model. The result indicates that the use of modular construction is associated with 85% schedule savings when all the modular risk factors have their minimum criticality values. Following the same procedure, the authors examined the second extreme condition, which includes having all the criticality values of the modular risk factors equal to 25. In this case, the predicted schedule savings take the maximum value, which is -0.01 (i.e., 1% schedule savings). Therefore, the conducted test reflects consistency in the predicted schedule savings under extreme inputs.

Afterward, the surprise behavior test is conducted to examine whether the predicted absolute values of schedule savings increase as the criticality values of the modular risk factors decrease and vice versa. The distribution functions derived using the *parametric distribution fitting* method have an inherent increasing behavior, and thus, they need not be examined. Therefore, the authors examined the increasing behavior of only the cumulative distribution functions that were derived using the *nonparametric distribution fitting* method (i.e., R29, R30, R31, and R34). To that respect, the derivative of their cumulative functions was calculated and presented in Fig. 8. As shown in the figure, the derivatives of the cumulative functions for R29, R30, R31, and R34 are strictly greater than zero over the entire data range. Therefore, the distribution functions fitted using polynomial models are monotonously increasing. Consequently, it can be concluded that as the criticality values of these modular risk factors increase, the values of $F(c)$ increase. On the other hand, the cumulative function for the schedule savings is monotonously increasing as well (Fig. 6). The latter reflects that higher criticality values shall yield to higher $\overline{F}$ or $F(S)$ and consequently to lower absolute values of schedule savings. Thus, as the criticality of modular risk factors increases in the project, the schedule savings associated with the use of modularization decrease. Ultimately, the model passes the surprise behavior test as its behavior mimics that of real-life situations.

Sensitivity Analysis

The authors further performed a sensitivity analysis to identify the modular risk factors and corresponding categories that are more influential on the schedule savings of modularization. First, the schedule saving of a base scenario needs to be calculated. To this

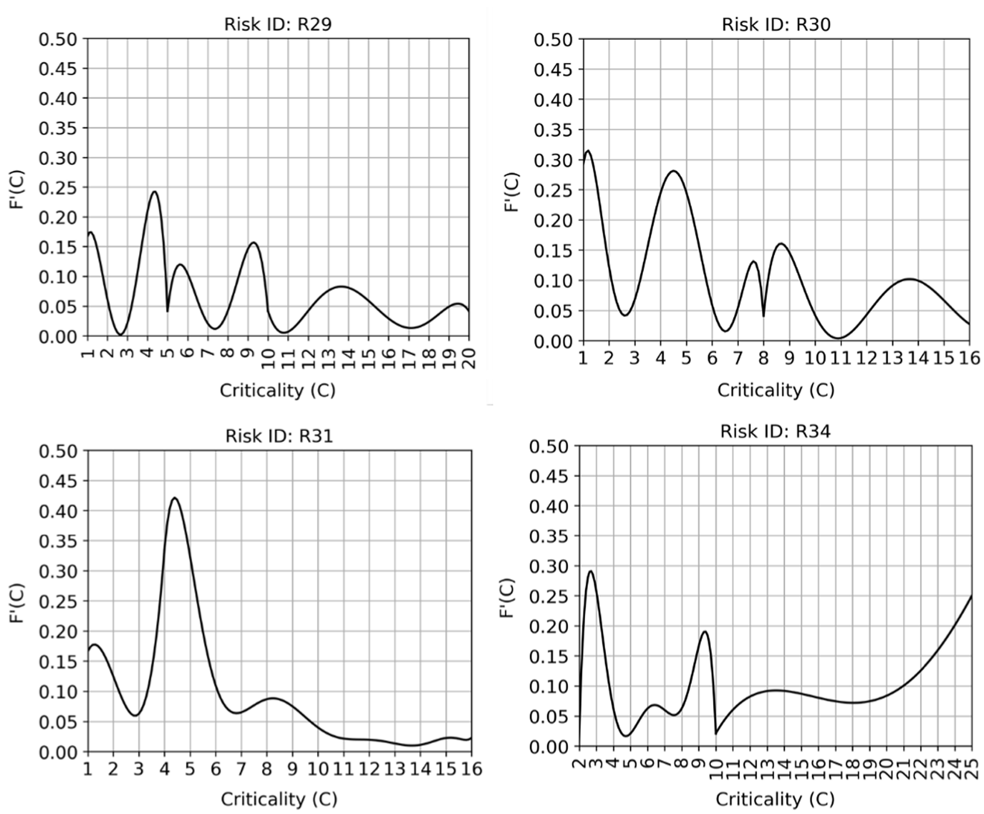

Fig. 8. Derivatives of the fitted nonparametric cumulative distributions.

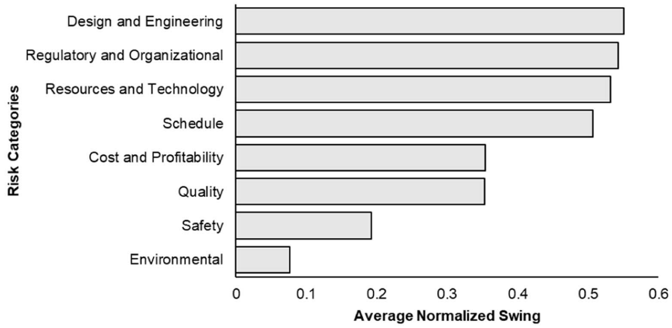

Fig. 9. Average normalized swing within each risk category.

end, the base scenario was established by setting the criticalities of all modular risk factors equal to 15. Keeping the criticality of all other modular risk factors at a value of 15, one modular risk factor R_i is varied at a time by applying a 30% decrease and increase in its criticality value. In other words, and for each modular risk factor R_i, the schedule savings are obtained at a criticality value of 10.5 (30% decrease) and 19.5 (30% increase) while keeping the criticality of all other modular risk factors equal to 15. The difference between the schedule savings at the lower and upper ends is then computed for each modular risk factor to calculate the swing (Dutta and Kishen 2020). The swing of a modular risk factor represents its influence on the captured schedule savings. The authors normalized the swing values by the maximum swing value and subsequently computed the average swing across the different risk categories (Fig. 9). As shown in the figure, design and engineering, regulatory and organizational, and resources and technology are the main influential project aspects that should be considered to maximize the schedule benefits of modular construction methods in the construction industry. The "Discussion of Research Results" section presents a detailed discussion of the influential risk categories.

Model Validation

Prior to validation, the developed model was automated in Excel Visual Basic for Applications (Excel VBA) by including all the derived weights, fitted cumulative distributions, equations, and established decision-making benchmarks. Therefore, the automation of the model was made so that the experts only assess the likelihood of occurrence and relative schedule impact without going through the other steps and mathematical calculations. All other steps are then automatically conducted by Excel VBA in a timely and efficient manner. Ultimately, the automated model provides project stakeholders with the following: (1) the schedule savings associated with the performed risk assessment, (2) the established decision-making benchmark for comparison and evaluation purposes, and (3) the top five modular risks that require careful attention in the project to ensure maximized capitalization on the schedule benefits of modularization. The validation of the process was comprised of two steps: (1) the experts first tested the model on actual ongoing projects; and (2) the experts then provided qualitative feedback related to the benefits, value, and comprehensiveness of the developed model.

Model Testing

The authors shared the developed model with multiple experts working at five leading companies in the US with an average of $2.45 billion annual business revenue. The developed model was examined by the industry experts on various new ongoing projects, different from those used for the development of the model. Furthermore, the industry experts tested the model on construction projects from different sectors, including commercial, building, and healthcare. To assure credibility and unbiasedness of the validation process, the developed model was tested by the project experts themselves rather than by the authors. For conciseness, the authors present the assessment results of only one construction project. The project is a multistory commercial building constructed using the modular approach. The main driver of adopting modularization in this project is to reduce the construction schedule and cost. Although the assessment is conducted on Excel VBA, the authors presented the detailed results to elaborate on how the results are being assessed in any project. The assessment results are shown in Table 2.

The project team conducted the risk assessment for the case study by rating the likelihood of occurrence and schedule impact of each modular risk in the project. Once the criticalities (second column of Table 2) are calculated, the tool automatically calculates the percentile level of each modular risk using graphs of Figs. 4 and 5. Afterward, the weighted percentile level is calculated using Eq. (9), which is 0.583 for this project. Ultimately, the schedule savings associated with the obtained weighted percentile level (i.e., 0.583) are then obtained using Fig. 6. The obtained schedule savings for the project case study are equal to 31.22%, which is approximately equal to the industry benchmark (31.7%). The latter indicates that the adoption of modularization in the project is similar to the industry average in terms of the captured schedule savings. However, proactive management can further improve the realized savings in the project.

Qualitative Feedback

Upon testing the model on various ongoing projects, the industry experts provided feedback on the developed model. Generally, the industry experts perceived the model to be comprehensive in terms of its integration of all the potential risk factors that could be associated with the use of the modular approach in construction projects. Although the schedule estimates may not be highly accurate, they constitute a reliable assessment for decision-making processes. Nevertheless, they perceived the developed model to constitute an efficient tool that assists the project team in examining schedule-related benefits and risks not only in the early stages of the project but rather during the execution stages. Such flexibility in use is believed to allow for monitoring the effect of any changes in project conditions or the emergence of available information on the expected schedule savings of modularization. In addition, their feedback emphasized the great potential and value of the developed model in highlighting the key schedule-related challenges, allowing proactive risk management. The industry experts also emphasized the practicality and high benefits of the developed model for the decision-making process and particularly during negotiations and discussions with the owner during the early phases of the project. However, the industry experts recommended the incorporation of positive risks and opportunities to allow for a more positive attitude toward modularization during feasibility analysis. In addition, they recommended having a feature that allows for the collaborative use of the model among the various project team members. The latter is perceived by the industry experts as important because it ensures alignment among the team members as related to the evaluation of the modular risk factors in the project. The authors addressed these recommendations and comments in the automated model to allow for the aggregation of multiple collaborative risk assessments conducted by the various project team members.

Given the conducted validation, the authors can assert that the developed risk assessment framework is effective at evaluating the

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captured schedule savings of modularization and helping project stakeholders proactively control the various influential risks in the project.

Discussion of Research Results

This section provides a detailed discussion on the top influential risk categories, including design and engineering (ranked 1st with an average normalized swing value of 0.55), regulatory and organizational (ranked 2nd with an average normalized swing value of 0.54), and resources and technology related issues (ranked 3rd with an average normalized swing value of 0.53).

Design- and Engineering-Related Risk Factors

Previous studies have extensively highlighted the importance of design- and engineering-related aspects in optimizing the use of modular construction. For instance, Jang and Lee (2018) conducted a productivity analysis on two different construction projects deploying offsite construction methods. The results of Jang and Lee (2018) indicated that the design of modules had a significant effect on the witnessed productivity improvements and, therefore, on the captured schedule savings. In fact, Arashpour et al. (2017) highlighted that the unsuitability of design for manufacturing, transportation, and assembly is one of the main risk factors affecting the performance of offsite construction projects. Nevertheless, adequate interfacing management of the modules during the design phase is essential to avoid schedule delays and disruptions that may be caused by imprecise tolerances (O'Connor et al. 2014). In addition, Bertram et al. (2019) highlighted that capturing the full schedule benefits of modular construction requires the optimization of design and the ability to achieve scale and repeatability.

Regulatory and Organizational Related Risk Factors

According to Said (2015), collaboration among project stakeholders (owner, designers, module suppliers, manufacturers, and contractors) helps in increasing the benefits associated with the use of offsite construction methods. Furthermore, Pan and Sidwell (2011) state that the cost and schedule reductions incurred by the adoption of offsite construction methods require an extensive commitment of the stakeholders and continuous exploration of this construction method in collaboration with their supply chains. On the other hand, contractual and technical requirements should favor the adoption of modular construction methods (O'Connor et al. 2015). According to Nadim and Goulding (2011), there is a need for new processes and contractual models for the implementation of offsite construction methods. Moreover, the use of collaborative agreements has been associated with maximized benefits of modular construction methods (Wong et al. 2017). Also, Arashpour et al. (2017) considered contractual disputes and problems a potential risk in projects integrated with offsite construction methods.

Resources and Technological Related Risk Factors

According to a study conducted by Jang and Lee (2018), productivity improvements associated with the use of modular construction methods are greatly dependent on the skill levels of laborers employed in the project. Nevertheless, Jaillon and Poon (2010) highlighted that the experience gained by the different stakeholders from previous projects could lead to more improvements in the project schedule. In fact, the knowledge gained through previous experience can be used in earlier stages of the project in order to obtain continuous improvements and cooperation between the different project parties (Larsson et al. 2014). On the other hand, site attributes and logistics are one of the main project characteristics affecting the feasibility and performance of modularization in construction projects. Site attributes and logistics include the following: (1) availability of space for storage and unloading of modules (Hwang et al. 2018), (2) site location from offsite facilities (Hwang et al. 2018), (3) accessibility of the transport/lifting equipment (Khalili and Chua 2013), and (4) suitability of onsite soil conditions for installation Arashpour et al. (2017).

Theoretical Contributions and Practical Implications

This research has theoretical contributions and practical implications. On the one hand, theoretically, this paper greatly contributes to the body of knowledge as it is the first of its kind to explore schedule savings from a proactive risk management perspective. Furthermore, this study is the first to explore the impact of various project risks on the schedule savings of modularization from a probabilistic approach, as well as model the realized schedule savings using data from actual construction projects. Such an approach allowed the authors to establish an assessment framework by enabling a ready comparison for industry practitioners between the project under evaluation and other modular construction projects in the industry. Finally, the theoretical contribution also includes the unprecedented development of an assessment benchmark for enhanced decision-making and risk control in modular construction projects.

On the other hand, practically, this paper identified key aspects and risk factors that should be considered in construction projects to optimize the schedule benefits of modular construction methods. In addition to that, the developed model offers industry practitioners the capability to conduct project-specific evaluations based on a comprehensive list of modular risk factors. The incorporation of a comprehensive list of modular risk factors allows for optimal use of available information in the project and, subsequently, a prospective assessment of schedule benefits. The assessment process was further accompanied by the establishment of a decision-making benchmark—which is equal to 31.70% of schedule savings—based on the industry average of risk criticalities. Thus, the developed model helps industry practitioners take enhanced decision-making by (1) highlighting the top risk factors and barriers affecting the realized schedule savings in their projects; and (2) comparing the schedule savings assessed for the project with the provided decision-making benchmark (i.e., industry-average schedule savings). To achieve that, industry practitioners are required to follow the five steps depicted in the section "Model Development and Formulation" of the methodology. Nevertheless, an automated tool was developed in which industry practitioners are only required to input the likelihood of occurrence and impact of each modular risk associated with the project under evaluation. Based on the provided model, proactive management can be achieved by helping practitioners take suitable mitigating strategies and corrective actions to optimize the schedule savings of modularization further. Nevertheless, the validation process conducted with industry experts revealed that the model not only aligns with the risk management practices in the construction industry but also adds a probabilistic dimension to the assessment and decision-making process. The latter was possible by capturing the variations in the perception of the modular construction market on the one hand and the various potential schedule savings that may be incurred in construction projects due to the use of modularization on the other.

Conclusion, Limitations, and Future Research Work

This paper developed a risk assessment framework that can assist project stakeholders' assessments of the realized schedule savings of modularization in the project and proactive control of the impact of associated risks. The goal of this paper was achieved by the following: (1) modeling the criticalities of 50 modular risk factors on the realized schedule savings using data collected from 48 industry professionals, (2) modeling the schedule savings associated with the use of modularization using data collected from 68 real modular construction projects, and (3) formulating an assessment model with a decision-making benchmark. Further, a sensitivity analysis was conducted showing that design and engineering, regulatory and organizational, and resources and technology related issues are the main aspects affecting the realized schedule savings of modularization in the construction industry. Ultimately, a decision-making benchmark was established to assist project stakeholders in taking proactive decisions and corrective actions, ensuring maximized capitalization on the schedule benefits of modularization in construction projects.

Any developed model possesses some limitations and drawbacks. In fact, the level of accuracy of this model is highly dependent on the representativeness of the collected samples and the appropriateness of the fitted probability distributions. However, given the small modular construction market (Velamati 2012) on the one hand and the expected low participation of construction professionals in online surveys on the other hand (Chatterjee et al. 2019), the collected sample size of 48 respondents is considered acceptable. Furthermore, such a reasonable limitation was addressed by having (1) an empirical and statistical validation of the sufficiency of the sample size; and (2) respondents' profiles with a wide range of experience in modularization and career. To this end, the developed model and decision-making benchmark still constitute a reliable framework for the evaluation and control of the various modular risks' impacts on the captured schedule benefits of modularization in construction projects. Another limitation is that this model—although it can be used for all types of modular construction projects—is more tailored for US commercial and building projects. The latter is due to having schedule savings data collected mainly from US modular construction projects pertaining to the commercial and building sector. In addition, the developed model does not take into consideration the possibility of correlations among the various modular construction risks.

Future research studies can further upgrade and/or improve the proposed framework by allowing an automatic update to the distributions of the risk criticalities whenever a new observation (i.e., a new project assessment) takes place. The latter shall further enhance the accuracy of the decision-making benchmark and thus the reliability of the evaluation process. Also, future research studies can incorporate features that reflect the correlation between the modular risks' impacts. Finally, a set of mitigating strategies and actions for the various modular risk factors can be established and then incorporated within the developed model. The latter shall further facilitate the decision-making and proactive management of modular risks to maximize the schedule benefits of modularization in the project.

Data Availability Statement

All data, models, and code generated or used during the study appear in the published article.

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