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System Dynamic Modeling to Study the Impact of Construction Industry Characteristics and Associated Macroeconomic Indicators on Workforce Size and Labor Retention Rate

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Abstract: Limited skilled labor has been one of the greatest challenges facing the construction industry. The COVID-19 pandemic has further exaggerated the already strained construction labor market, leading to an additional negative impact. One of the major contributors to skilled labor shortages in construction is the issue of labor retention. Overall, this is a complex and dynamic situation that requires effective and efficient simulation-based techniques to capture the interdependent relationships that affect the performance of the construction labor market. This paper fills this knowledge gap. To this end, the authors used a multistep research methodology that involved (1) identifying factors that affect skilled labor shortages; (2) developing a one-module system dynamics model that consists of three interconnected systems (namely, construction labor market system, industry characteristics system, and economic conditions system); (3) initializing and calibrating the model to simulate the construction labor market; (4) validating the model through structural, behavioral, and calibration tests; and (5) conducting sensitivity analysis to simulate different parameters and examine their impact on skilled labor shortage. Among other findings, results indicated that all scenarios were successful in improving the conditions of the skilled labor market by increasing the workforce size and labor retention rate. Further, the model demonstrated that economic indicators have a more impactful influence on labor retention patterns compared with industry characteristics. The developed model offers industry practitioners, policymakers, business analysts, and other associated stakeholders a useful tool to test various scenarios including national-level economic policies and labor retention regulations that affect the construction skilled labor market. Consequently, this allows users to analyze the impact of variables such as fiscal policies, economic support plans, and construction spending strategies. **DOI: 10.1061/JCEMD4.COENG-13410.**

Introduction

Limited skilled labor has been one of the greatest challenges facing the construction industry. The industry began experiencing this shortage in the 1980s, and it has continued with a repetitive cyclic trend over the last 4 decades (Sawyer and Rubin 2007). In 2018, the Association of General Contractors of America (AGC) reported that 80% of general contractors have problems hiring enough skilled craft workers to match the level of demand (AGC 2018). This shortage can be contributed to a combination of challenges including the increasing average age of construction workers currently in the market, the decreasing rate of young skilled construction labor joining the industry (Karimi et al. 2018), and the long-term effects of the global financial crisis (Dufour and Orhangazi 2014). Such challenges were further exaggerated with the advent of the COVID-19 pandemic, leading to an additional impact on the already strained construction labor market (Brinca et al. 2021).

One of the major contributors to skilled labor shortages in construction is the issue of labor retention. The construction industry is known for its deficiency in retaining skilled labor due to two major contributors. The first contributor is related to the arduous characteristics of the construction industry that might repel workers from joining or continuing to work in the industry. Such characteristics include low wages (Olsen et al. 2012), lack of training (Kashiwagi and Massner 2002), poor industry image (Castañeda et al. 2005), and nature of the work (Welfare et al. 2021). The second contributor is related to factors external to the industry. One such major external factor is the underlying economic conditions within which the industry is operating (Karimi et al. 2018). The literature supports the existence of a correlation between economic indicators and the performance of the construction labor market (Lukianenko 2016). To that end, a holistic examination of skilled labor shortages should take into account factors that are innate within the industry on one hand, and external economic factors that affect the industry on the other.

Owing to the dynamic nature of the construction industry, the construction labor market is also dynamic, and thus its state changes over time (Assaad and El-adaway 2021). Moreover, it is viewed that the factors influencing the number of skilled workers entering, participating in, and exiting the construction industry are highly interdependent, so that a change in one factor can impact others (Sing et al. 2016). Therefore, simulation-based techniques that are able to capture the relationships between these factors as well as their impact on the construction labor market over time are more suitable

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for examining the issue of skilled labor shortage (Kim et al. 2019). One such approach is system dynamics (SD) modeling.

Although the issue of skilled labor shortages in the construction industry has been extensively studied, there has been comparatively little focus on examining it using SD. Further, the interdependent relationships between industry characteristics and economic indicators and their impact on skilled labor retention have not been fully explored. The authors believe that the adoption of SD modeling would enable the capturing of the complex dynamics of the construction labor market and the factors that affect the retention of skilled labor. Furthermore, SD would allow for the integration of factors external to the industry such as macroeconomic indicators that impact the labor market (Li et al. 2020).

Goal and Objectives

The goal of this paper is to study the collective impact of key characteristics of the construction industry and associated macroeconomic indicators on the workforce size and retention of labor. To this end, the associated objectives include (1) identifying key construction characteristics and economic conditions related to skilled labor shortages, (2) formulating the links relating the identified factors to one another and establishing the dynamic relationships connecting such factors to the retention rate of skilled workers in the industry, and (3) assessing the sensitivity of the construction skilled workforce size to various industry and economic conditions.

Relevant Background Information

This section presents previous studies that focused on (1) system dynamic models that addressed the issue of skilled labor shortage in construction; and (2) economic indicators highly correlated with the performance of the construction labor market.

SD Modeling of Labor Shortage

SD is a modeling technique that enables the analysis of complex systems (Leon et al. 2018). Complex systems are systems whose state changes over time and consist of many components that may interact with each other (Sterman 2000). Construction labor management can be classified as a complex dynamic system, because it is (1) extremely complex, consisting of multiple interdependent components; (2) highly dynamic; (3) contains multiple feedback processes; and (4) involves nonlinear relationships (Sterman 2000). As a result, system dynamics modeling has become increasingly popular for simulating construction labor systems, e.g., labor productivity (Gerami Seresht and Fayek 2018), labor safety (Nasirzadeh et al. 2018), labor supply (Sing et al. 2012), and labor rewards (Azeez et al. 2019).

Nonetheless, less focus has been directed toward utilizing SD in modeling skilled labor shortages. Sing et al. (2016) developed a SD model that focused on forecasting and planning labor requirements for infrastructural projects. The model consists of three main submodels: labor demand forecasting, labor supply forecasting, and identification of workforce surplus or shortage from these forecasts. However, the model is a simplified attempt to simulate the complexities of the real-world supply and demand dynamics. It requires a more detailed representation of key parameters such as construction workers leaving the industry, as well as considering other skilled trades to account for long-standing workforce problems such as skill mismatches (Sing et al. 2016).

Furthermore, Kim et al. (2019) used SD modeling to examine the causes and impacts of skilled labor shortages. The model simulates the flow of skilled labor at the project level to understand the inherent complexities of labor shortage scenarios and clarify the causes and impacts of such shortages on project performance. The study used five different scenarios to simulate shortages and measure corresponding construction project behaviors. Nevertheless, the model treats skilled labor from all trades and all types of construction projects as one. Accordingly, it does not consider the particular types of crafts, the level of difficulty in different domains, and the different types of construction projects (Kim et al. 2019).

Abbaspour and Dabirian (2019) designed an SD model that simulated a project's workflow. The model calculates the amount of desired labor for a given project based on the amount of work determined by the workflow stocks and the average productivity of labor. Factors such as hiring and turnover rates were also considered to be able to examine the supply and demand dynamics of labor. Overall, the model allowed the assessment of different labor hiring policies for construction projects. However, similar to Kim et al.'s (2019) model, it does not account for the different types of trades and construction projects (Abbaspour and Dabirian 2019).

Lastly, Lukianenko (2016) built a SD simulation model of the Ukrainian labor market. The model consisted of two interconnected submodels, one representing labor supply and the other labor demand. Potential scenarios were examined by changing the values of key indicators of the labor market and examining their impact on one another. Further analysis using the model allowed for the identification of medium-term strategies for a growing labor market as well as the impact of major labor market indicators on macroeconomic stabilization of the Ukrainian economy. However, the study did not provide sufficient details on how the model was validated and how further research can be extended to improve the performance of some parameters such as removing the rigidity of labor wages (Lukianenko 2016).

As such, it can be seen that a few studies have used SD modeling to address skilled labor shortages in the construction industry. Table 1 summarizes the scope of work and key construction factors used in the preceding literature related to SD modeling of labor shortage.

Economic Indicators

Economic indicators possess information that is critical for studying the development of economic sectors, such as the construction industry (Sing et al. 2015). This has been corroborated by the magnitude of research that has explored the relationship between key economic factors and construction industry performance. For example, some studies have investigated the effect of economic indicators on construction spending and investment decisions in construction projects (Sing et al. 2015). In such studies, macroeconomic indicators were used to predict construction output and the value of construction works completed by contractors (Yiu et al. 2004). Such indicators include interest rate, gross domestic product (GDP), money supply, consumer price index, labor force, unemployment rate, construction price, real interest rate, and building material price index (Killingsworth 1990; Goh 1996; Akintoye and Skitmore 1994; Sing et al. 2015).

Other studies have focused on the relationship between economic factors and construction costs. For example, Shiha et al. (2020) developed machine learning models to predict the impact of economic variables such as the exchange rate, inflation rate, and GDP growth rate on the price of construction materials in Egypt. Similarly, Shahandashti and Ashuri (2016) used economic variables such as inflation rate, consumer price index, construction spending, and GDP, among others, to develop a vector error correction model for forecasting highway construction costs. Other papers used other

Table 1. Previous studies in relation to SD modeling of labor shortages

References	Scope of work	Key construction factors used
Sing et al. (2016)	Developed a SD model for determining the required workforce in infrastructure projects to optimize workforce planning and minimize project costs.	Current stock of labor; potential new entrants; training policy; recruitment rate; enrollment in training; retirement rate; current stock of projects; vacancy rate.
Kim et al. (2019)	Created a SD model to assess the impact of skilled labor shortage on labor wages and project performance.	Average duration of employment; average layoff time; cost overrun; desired labor; entering rate; jobsite safety; labor wage; productivity; project budget; project cost; project duration; quit rate; skilled labor.
Lukianenko (2016)	Built a SD model that simulates the demand and supply formation on the Ukrainian labor market taking into consideration key economic indicators.	Youth unemployment; experienced unemployment; total unemployment; hiring time; hiring rate; quit rate; retirement rate; labor force; desired employment; productivity; expected demand.
Abbaspour and Dabirian (2019)	Presented a system dynamics model to assess different labor hiring policies and their impact on project performance.	Total labor; labor need; skilled labor hiring; labor productivity; nonskilled labor hiring; labor shortfall; expected project delays; work in progress; rework; labor cost.

factors such as average hourly earnings, consumer price index, Dow Jones industrial average, employment levels, foreign exchange rate, GDP, GDP construction, GDP growth rate, and inflation rate (Shahandashti and Ashuri 2013, 2016; Faghih and Kashani 2018; Ng et al. 2007; Ernest et al. 2019; Cao et al. 2015; Olatunji 2010; Shiha et al. 2020).

The literature also includes papers that incorporated economic indicators into project planning practices, such as maintenance scheduling and postdisaster recovery planning (Ghannad et al. 2020; Eid and El-adaway 2017). Such papers predominantly utilized economic factors that include employment level, construction labor wage, household value, and construction trust fund contributions (Ahmadi and Shahandashti 2020; Ghannad et al. 2020; Eid and El-adaway 2017; Nobrega and Stich 2012).

Despite the aforementioned efforts, limited research has examined the impact of economic indicators on skilled labor shortage. For instance, Kim et al. (2019) studied the causes and effects of skilled labor shortages in construction projects and identified economic conditions such as initial wage, average labor wage, and unemployment rate as factors that affect the entry rate of skilled labor into the construction market. Sing et al. (2016) investigated how industry characteristics and key economic conditions influence the construction workforce gap. Macroeconomic indicators such as interest rate, national GDP, government funding for craft training, and property price index were found to be highly associated with workforce supply. Lukianenko (2016) pointed out the existing link between macroeconomic and industry-related conditions in the construction labor market and used econometric modeling to simulate the formation of labor supply and demand. The study included economic factors such as unemployment level, unemployment rate, GDP, expected GDP, nominal wage, labor–income ratio, and capital-labor ratio (Lukianenko 2016).

Rasdorf et al. (2016) identified essential economic and construction industry variables for labor demand forecasting, in which interest rates, material prices, construction output, and real wages were found to be significant. Ho (2016) investigated strategies for resolving labor and skill shortages and concluded that increasing labor wages is an effective strategy to alleviate skilled labor shortages. It is worth noting that analyzing the influence of economic circumstances on the workforce is not confined solely to the construction domain but is also prevalent in the economic field. In fact, Li et al. (2020) explored the relationship of wage differences, price differences, and technology gaps with relative employment on one hand and with labor flow on the other. Ultimately, the literature highlights the value of using economic indicators to gain a better understanding of the performance of the construction labor market. Table 2 summarizes the key economic factors used in previous studies discussing labor shortages.

Although the issue of skilled labor shortage has received significant attention from researchers, considerably less focus has been directed toward modeling it using simulation-based techniques such as SD (Li et al. 2020). Moreover, the literature indicates a significant correlation between economic factors and the performance of the construction labor market (Lukianenko 2016). However, it falls short in exploring the various economic indicators and their impacts on the construction labor market. To this end, this paper uses a SD modeling approach to simulate the dynamic and interdependent relationships between industry characteristics and economic indicators to examine their integrated impact on the retention of skilled labor in the construction market.

Table 2. Economic indicators in previous labor shortage studies

Economic indicator	References
Labor wage/nominal wage/real wage/initial wage	Sing et al. (2016); Kim et al. (2019); Lukianenko (2016); Rasdorf et al. (2016); Abbaspour and Dabirian (2019); Li et al. (2020); Dube et al. (2016); Boffy-Ramirez (2022); and Andriopoulou and Karakitsios (2022)
Interest rate	Sing et al. (2016) and Rasdorf et al. (2016)
Unemployment rate/unemployment level	Kim et al. (2019); Lukianenko (2016), Li et al. (2020); Dube et al. (2016); and Andriopoulou and Karakitsios (2022)
GDP/expected GDP	Sing et al. (2016); Lukianenko (2016); and Andriopoulou and Karakitsios (2022)
Material prices	Sing et al. (2016) and Rasdorf et al. (2016)
Price difference	Li et al. (2020)
Construction output	Rasdorf et al. (2016)
Labor income ratio	Lukianenko (2016)
Capital labor ratio	Lukianenko (2016)

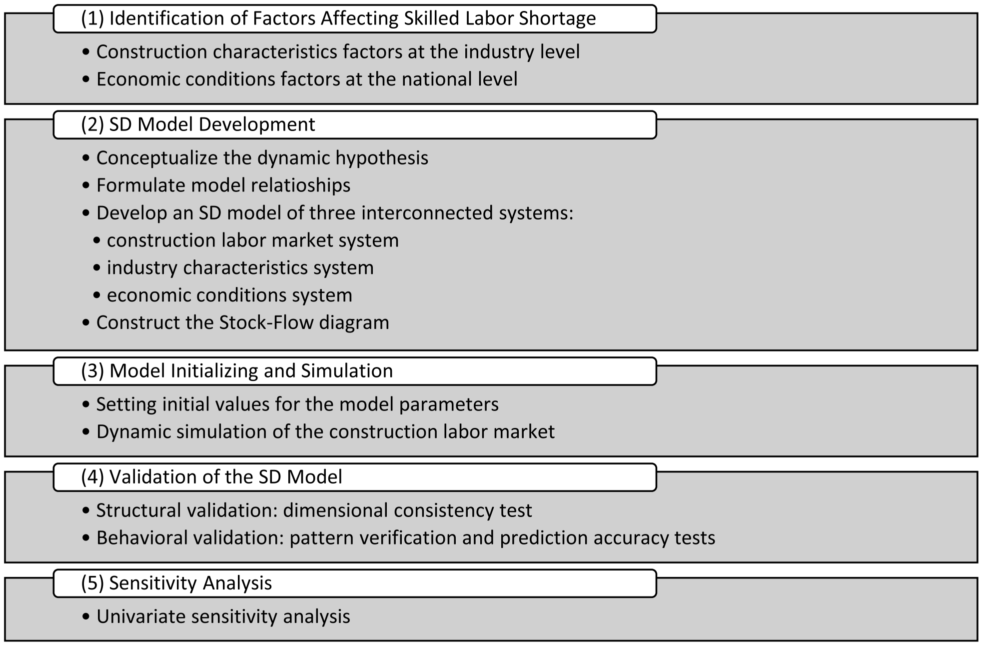

Fig. 1. Research methodology.

Methodology

To achieve the goal and objectives of this paper, the authors used a multi-step research methodology as shown in Fig. 1. The following subsections explain the methodological steps.

Identification of Factors Affecting Skilled Labor Shortage

In the first step, the factors influencing the shortage of skilled labor were identified through a literature review. The literature contains many studies that discussed the factors that affect skilled labor shortage at different levels including macrolevel and microlevel. Macrolevel factors include organizational-level, industry-level, and national-level factors, and microlevel factors include trade-level, activity-level, and project-level factors. This paper focuses on two types of factors that affect skilled labor shortages: (1) construction characteristic factors that are at the industry level; and (2) economic conditions factors at the national level.

Construction characteristics factors are industry features related to the labor market that influence the conditions of skilled construction workers. On the other hand, economic conditions factors are macroeconomic indicators that represent the influence of the economy on the construction labor market operating within this economy. To this end, 17 industry-level construction characteristics factors and seven national-level economic conditions factors were identified through the literature. Construction characteristics factors were identified through the following studies: Choi et al. (2022), Ahmed et al. (2022), Metro et al. (2021), Assaad and El-adaway (2021), Chan et al. (2020), Ayodele et al. (2020), Holtom et al. (2008), and Sing et al. (2012). On the other hand, economic conditions factors were identified through the following studies: Sing et al. (2015), Shiha et al. (2020), Delvinne et al. (2020), Albattah et al. (2019), Nobrega and Stich (2012), Shahandashti and Ashuri (2016), Levanon et al. (2014), and Lukianenko (2016). The following subsection provides detailed information regarding the identified factors and their use within the context of the developed system dynamics model.

SD Model Development

In this step, the authors developed a one-module SD model that examines the complex cause-and-effect relationships associated with skilled labor shortages in the construction industry. It captures the interdependencies of key economic and construction factors related to labor shortage as identified from the literature. Then, it relies on real-world country-level data to simulate the behavior of these factors over time. The model focuses on the factors that impact the rate of retention of skilled labor within the industry. However, it also includes other parameters that emulate how construction workers enter, retire, get laid off, and get rehired in the market.

Dynamic Hypotheses

In system dynamics modeling, dynamic hypothesis is the process of developing a conceptual framework for the dynamic behavior of model relationships (Nasir and Hadikusumo 2019). It is the foundation for model formulation; thus, it is important that it is based on a real phenomenon (Mortazavi et al. 2020). A broad model boundary is preferred over great detail to ensure that all important structures are included rather than a detailed representation of variables (Sterman 2000). In this study, it was imperative for the authors to design the SD model such that it includes the key construction characteristics and economic conditions identified from the literature. It was also important that the design allows for the interaction between the economic factors and the construction industry factors. These considerations led to the following set of hypotheses:

H1: In the construction labor market, skilled workers enter the market upon completion of trade/vocational training and exit the market by retiring. Along this life cycle, the percentage of skilled labor who opt to continue working in the construction industry, also known as the retention rate, is impacted by a number of factors that are related to the nature of the industry as well as the economic environment in which the industry operates.

H2: The flow of skilled labor within the labor market is influenced by key features of the construction industry. The better the performance of the industry in relation to these features, the more likely it is that skilled workers will remain in the industry, leading to a higher labor retention rate. For example, if the industry offers competitive wages and benefits, it can attract and retain a skilled workforce.

H3: The flow of skilled labor within the labor market is influenced by the economic conditions that are external to the construction sector. Similarly, the better the performance of the economy in terms of key macroeconomic indicators, the more likely that skilled workers will remain in their current jobs, leading to a higher labor retention rate.

These dynamic hypotheses were used as the theoretical base upon which the SD model was developed. Each of the hypotheses materialized into a complete system. As such, the SD model in this paper consists of three systems: (1) construction labor market system, (2) industry characteristics system, and (3) key economic conditions system.

SD Model Relationships

Two types of relationships were used to link components of the SD model to one another: hard relationships and soft relationships. Hard relationships are those that connect variables based on equations with known mathematical formulas (Gerami Seresht and Fayek 2018). For example, Eq. (1) demonstrates the hard relationship that links the rate of workers leaving their current jobs with the construction industry's quitting and layoffs rates

$$\text{Rate of leaving current job}\left(\frac{\text{number of workers}}{\text{months}}\right) = \text{Layoffs rate}\left(\frac{\text{number of workers}}{\text{months}}\right) + \text{Quitting rate}\left(\frac{\text{number of workers}}{\text{months}}\right) \quad (1)$$

On the other hand, soft relationships are mathematical equations that are developed using statistical techniques. They are often based on expert knowledge or understanding of real-world systems (Gerami Seresht and Fayek 2018). In this study, soft relationships were inferred from the literature. Then, they were developed into mathematical equations through multiple regression. Past data from multiple reliable sources were utilized to apply regression to quantitatively establish correlation between an output variable and input variables (Sing et al. 2016; Warner 2013). The general form of multiple regression is shown in Eq. (2)

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \quad (2)$$

In the SD mode developed in this paper, some of the identified factors were connected using hard relationships in a manner similar to that described in Eq. (1). The remainder of the factors were linked through soft relationships using multiple regression as demonstrated in Eq. (2). The following subsections detail the architecture and dynamics relationships in each of the systems of the SD model.

Construction Labor Market System

The first system in the SD model describes how the construction workforce flows throughout the labor market. It simulates the behavior of skilled workers from when they finish their trade/vocational training and enter the market when they retire working in the industry. The system consists of three stocks: (1) newly hired workers, (2) workforce size, and (3) unemployed experienced workers. Each stock represents the cumulative size of the construction workforce at a certain stage of the workers' careers. To connect these stocks, six flows were created to introduce the rate of increase/decrease in the stocks: entering market, labor retention rate, leaving current job, rehiring, and two retiring flows. Details regarding the SD elements created in this system, their types, and the equations used to define their relationships are presented in Table 3.

In the construction labor market system, the inflow of skilled labor is determined by the number of students who graduate from trade/vocational schools as skilled workers each year. These fresh graduates are represented in the model by the education and training parameter. It was assumed that skilled students graduate at a yearly rate, then enter the workforce market if hired. Accordingly, the entering market flow is dependent on the industry's hiring rate, and its equation is triggered once every 12 time steps (Table 3). Hired students enter the construction workforce and are represented in the model by the newly hired workers stock.

After getting involved in the construction industry, skilled workers decide whether to continue working in the industry based on a labor retention rate. A high labor retention rate reflects a healthy industry that aims to preserve skilled labor within its labor market. Retention of skilled labor can enhance productivity, reduce turnover costs such as recruitment and retraining costs (Lingard 2003), and allow for the accumulation of knowledge and expertise (Chih et al. 2018).

By investigating the literature, the authors were able to identify the factors and underlying drivers behind construction workers' retention. In this research, the labor retention rate was influenced by various industry and economic factors including average yearly wage, benefits to income ratio, rate of weekly hours worked, and best alternative opportunity. In the SD model, multiple regression was used to determine the relationship between retention rate and these factors. The form of the regression equation used to calculate the labor retention rate is provided in Table 3. The higher the labor retention rate, the higher the rate of increase in the workforce size. As such, the workforce size stock corresponds to the number of skilled laborers who remain involved in the industry.

The rate of change of the workforce size depends on the labor retention rate as an inflow and the rates of workers retiring or leaving their current jobs as outflows. In the SD model, skilled workers in the workforce size stock population can either retire or leave their jobs. Retiring workers exit the system of the model in accordance with the industry's retirement rate. Workers who leave their jobs may also choose to retire. Otherwise, they can look for jobs and get rehired again. The unemployed experienced workers stock represents the population of workers leaving their jobs because they either opted to quit or got laid off. Accordingly, the leaving current job flow is the summation of the construction industry's layoffs and quitting rates as retrieved from the US Bureau of Labor Statistics (US Bureau of Labor Statistics 2021).

The proportion of experienced workers who are rehired after leaving their jobs is based on the industry's employment rate, and their count is accounted for in the newly hired workers. It is known that employers in the construction market prefer experienced skilled workers over workers who recently graduated from vocational schools. The SD model was configured to mirror such facts by assigning the pool of experienced workers (represented by the unemployed experienced workers stock's having higher priority in hiring in comparison with inexperienced skilled labor.

Industry Characteristics System

The construction labor market system described in the preceding subsections needs inputs in order to be adjusted for different circumstances and scenarios. To that end, the industry characteristics system was created to introduce the impact of key features of the construction industry on the skilled labor market. The system focuses mainly on factors that impact the rate of retention of skilled labor within the industry. However, it also includes other parameters that control the rate at which skilled construction workers enter,

Table 3. System elements, types, and equations of the construction labor market system

Element name	Element type	Relationship type	Mathematical equation/description
Education and training	Parameter	—	Number of students who graduate from trade/vocational schools as skilled workers each year (Barshay 2021).
Entering market	Flow	Hard	Entering market $\left(\frac{\text{number of workers}}{\text{months}}\right)$ = Education and training $\left(\frac{\text{number of workers}}{\text{months}}\right) \times$ Hiring rate $\left(\frac{\text{number of workers}}{\text{months}}\right)$
Newly hired workers	Stock	Hard	Newly hired workers (number of workers) = $\int$ Entering market $\left(\frac{\text{number of workers}}{\text{months}}\right) +$ Rehiring $\left(\frac{\text{number of workers}}{\text{month}}\right) -$ Labor retention rate $\left(\frac{\text{number of workers}}{\text{month}}\right) \times dt$ (month)
Labor retention rate	Flow	Soft	Labor retention rate = $\beta_0 + \beta_1$ Average yearly wage $+ \beta_2$ Best alternative opportunity $+ \beta_3$ Adjusted yearly wage $+ \beta_4$ Benefits to income ratio $+ \beta_5$ Rate of weekly hours worked
Workforce size	Stock	Soft	Workforce size (number of workers) = $\int \beta_0$ [Labor Retention rate $\left(\frac{\text{number of workers}}{\text{month}}\right) -$ Retiring $\left(\frac{\text{number of workers}}{\text{month}}\right) -$ Leaving current job $\left(\frac{\text{number of workers}}{\text{month}}\right)$] $+\beta_1$ Time^3 $+$ β_2 Time^2 $+ \beta_3$ Time. dt (month)
Retiring	Flow	Hard	Retiring $\left(\frac{\text{number of workers}}{\text{month}}\right)$ = Retirement rate $\left(\frac{\text{number of workers}}{\text{month}}\right)$
Leaving current job	Flow	Hard	Leaving current job $\left(\frac{\text{number of workers}}{\text{month}}\right)$ = Layoffs rate $\left(\frac{\text{number of workers}}{\text{month}}\right)$ + Quitting rate $\left(\frac{\text{number of workers}}{\text{month}}\right)$
Unemployed experienced workers	Stock	Hard	Unemployed experienced workers (number of workers) = $\int$ Leaving current job $\left(\frac{\text{number of workers}}{\text{month}}\right) -$ Retiring 1 $\left(\frac{\text{number of workers}}{\text{month}}\right) -$ Rehiring $\left(\frac{\text{number of workers}}{\text{month}}\right)$. dt (month)
Retiring 1	Flow	Hard	Retiring 1 $\left(\frac{\text{number of workers}}{\text{month}}\right)$ = Retirement rate $\left(\frac{\text{number of workers}}{\text{month}}\right)$
Rehiring	Flow	Hard	Rehiring $\left(\frac{\text{number of workers}}{\text{month}}\right)$ = IF (unemployed experienced workers > 1), (1 − unemployment rate), 0)

retire, get laid off, and get rehired in the market. Variables in this system include unemployment rate, hiring rate, average yearly wage, benefits to total income ratio, retirement rate, quitting rate, layoffs rate, union–nonunion ratio, average weekly hours worked, and supply–demand ratio. A full list of the SD elements created in the industry characteristics system and details about their types and the equations used to define their relationships are presented in Table 4.

To simulate the influence of the construction industry on skilled labor, the variables in this system are all based on industry specific statistics. For example, the construction hiring rate was used in the SD model to represent the entry rate of skilled workers who recently graduated from vocational/trade schools into the construction labor market. On the other hand, the retirement rate is the percentage of skilled workers leaving the workforce. Thus, it represented the rate of exiting the construction labor market and thus the SD model. Other industry-related variables include the rate of leaving current job, which is the summation of the quitting rate and the layoffs rate of construction workers. Lastly, the rate of rehiring unemployed experienced workers is represented by the industry's employment rate (1 minus the unemployment rate).

As previously mentioned, the labor retention rate is dependent on both industrial and economic factors. The industrial factors that were used to determine the rate of retention of skilled labor in the industry include average yearly wage, benefits to income ratio, and rate of weekly hours worked. The average yearly wage is the average total earnings of construction workers in a year, excluding benefits, and other services (US Bureau of Labor Statistics 2021). In the SD model, the average yearly wage variable was calculated based on a number of input variables that included net job gains, average yearly wage for all workers, supply–demand ratio, and "union–nonunion ratio. The relation between the average yearly wage and the input variables was established using multiple regression. The form of the regression equation is provided in Table 4.

The benefits to income ratio variable describes the value of construction workers' benefits as a percentage of their average total compensation (US Bureau of Labor Statistics 2021). Findings of previous research papers indicated that investment in the income benefits and services offered to skilled labor are perceived favorably by construction workers and promote their willingness to remain in the industry (Azeez et al. 2019). The rate of weekly hours worked is a measure of the average number of hours that construction workers work per week. It was assumed that extended working hours, specially above 40 h per week, have an inversely proportional relationship with labor retention rate.

In the construction market, it is rarely the case that labor supply and labor demand are in equilibrium (Ho 2010). Theoretically, this

Table 4. System elements, types, and equations of the industry characteristics system

Element name	Element type	Relationship type	Mathematical equation/description
Hiring rate	Parameter	—	Number of newly hired workers as a percentage of the total construction labor force (US Bureau of Labor Statistics 2021)
Unemployment rate	Parameter	—	Number of unemployed workers as a percentage of the total construction labor force (US Bureau of Labor Statistics 2021)
Gross job gains	Parameter	—	Number of all worker employment increases at either opening or expanding establishments (US Bureau of Labor Statistics 2021)
Gross job losses	Parameter	—	Number of all worker employment losses at either closing or shrinking establishments (US Bureau of Labor Statistics 2021)
Net job gains	Variable	Hard	Net job gains (number of workers) = Gross job gains (number of workers)–Gross job losses (number of workers)
Union–nonunion ratio	Parameter	—	Number of workers belonging to unions as a percentage of the total construction labor force in a given month (US Bureau of Labor Statistics 2021)
Construction spending	Parameter	—	Amount of monthly expenditure in USD directed toward the construction industry, regardless of when the projects take place or payments are to contractors (Merryman 2010)
Labor content per USD	Variable	Hard	Labor content per USD $\left(\frac{\text{number of workers}}{\text{USD}}\right)$ = Workforce size (number of workers)/GDP construction (USD)
Demanded workforce size	Variable	Hard	Demanded workforce size (number of workers) = Labor content per USD $\left(\frac{\text{number of workers}}{\text{USD}}\right) \times$ Construction spending (USD)
Supply–demand ratio	Variable	Hard	Supply–demand ratio = Workforce size (Number of workers)/Demanded workforce size (number of workers)
Average yearly wage	Variable	Soft	Average yearly rate = $\beta_0 + \beta_1$ Net job gains $+ \beta_2$ Average yearly wage all workers $+ \beta_3$ Supply–demand ratio $+\beta_4$ Union–nonunion ratio
Benefits to total income ratio	Parameter	—	Construction workers' total benefits as a percentage of the average total compensation (US Bureau of Labor Statistics 2021)
Retirement rate	Parameter	—	Number of retired workers as a percentage of the total construction labor force in a given month (US Bureau of Labor Statistics 2021)
Quitting rate	Parameter	—	Number of workers quitting their jobs as a percentage of the total construction labor force in a given month (US Bureau of Labor Statistics 2021)
Layoffs rate	Parameter	—	Number of workers who got laid off as a percentage of the total construction labor force in a given month (US Bureau of Labor Statistics 2021)
Average weekly hours worked	Parameter	—	Number of hours per week the average construction worker works in a given month (US Bureau of Labor Statistics 2021)
Rate of weekly hours worked	Variable	Hard	Rate of weekly hours worked $= 40 \left(\frac{\text{hours}}{\text{week}}\right)$/Average weekly hours worked $\left(\frac{\text{hours}}{\text{week}}\right)$

means that the market is often alternating between states of labor shortages and labor surpluses. According to the law of demand, when the demand for skilled workers surges above the supply, labor wages increase. Similarly, when the demand for labor is below the supply, wages decrease (Ling et al. 2022). To capture the relationship between the law of demand and labor wages in the SD model, a supply–demand ratio variable was created. Using the workforce size stock to represent labor supply and the demanded workforce size variable to represent labor demand, the supply–demand ratio variable was created in accordance with the equation provided in Table 4. This variable expresses the count of available skilled labor in the market as a proportion of the amount of skilled labor that the industry demands at a given period of time.

To calculate labor demand in the model, the labor content per USD was multiplied by construction spending. Construction spending is the expenditure directed toward the construction industry in a given period of time, regardless of when projects take place or payments are to contractors (Merryman 2010). The labor content per USD was derived from the number of skilled workers in the market at a given point in time divided by the corresponding GDP construction for the same period. Sing et al. (2016) used a similar approach to estimate the labor demand for each work trade. Moreover, the supply–demand ratio was also used to estimate the adjusted labor wage, which is discussed in further detail in the following subsection.

Economic Conditions System

Although the variables in the industry characteristics system stem from within the construction industry, variables in the economic conditions system are external to the construction sector. Nonetheless, they are perceived to have a considerable impact on skilled labor shortages. The economic conditions system consists of variables related to key macroeconomic indicators at the national level. It simulates the influence of the state of the economy on the construction labor market operating within such an economy. The economic indicators in this system are closely related to the wages of skilled labor. This means that they affect the construction industry in terms of its ability to retain workers through sustainable labor wages. As such, the economic conditions system includes variables such as GDP construction, labor income share, labor income, consumer price index (CPI), adjusted yearly wage, and best alternative opportunity. A full list of the SD elements created in the economic conditions system, as well as details about their types and the equations used to define their relationships, are presented in Table 5.

Previous studies have highlighted the strong relationship between the value of construction and the growth rate of national GDP (Barber and El-adaway 2013; Qifa 2013). Accordingly, GDP construction was added to the economic conditions systems as one of the variables. It measures the output of the construction industry at a national level in a given month (US Bureau of Labor Statistics 2021).

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Table 5. System elements, types, and equations of the economic conditions system

Element name	Element type	Relationship type	Mathematical equation/description
GDP construction	Parameter	—	Contribution of the construction industry to overall GDP of the US in a given month (US Bureau of Labor Statistics 2021)
Labor income share	Parameter	—	Part of the national output of the construction industry allocated to workers' wages as a percentage of the total construction industry output (GDP construction) (US Bureau of Labor Statistics 2021)
Consumer price index (CPI)	Parameter	—	Relative price changes of a basket of goods and services over 2 consecutive years (US Bureau of Labor Statistics 2021)
Labor income	Variable	Hard	Labor income (USD) = $\left(\text{GDP construction (USD)} \times \text{Labor income share (\%)} \times \frac{1}{\text{CPI}}\right) \Big/$ workforce size (number of workers)
Adjusted yearly wage	Variable	Hard	Adjusted yearly wage (USD) = {Labor income (USD) − [Benefits to total income ratio (%) × Labor Income (USD)]} × Supply–demand ratio (%)
Average yearly wage all workers	Parameter	—	Average total earnings of all workers (in production and nonsupervisory roles) across the US in a year, excluding benefits and other services (US Bureau of Labor Statistics 2021)
Best alternative opportunity	Variable	Hard	Best alternative opportunity = Average yearly wage all workers (USD)/Average yearly wage (USD)

Other variables include labor income, which is the proportion of GDP that is given to labor as wages, and social benefits transfers (Wei et al. 2012). In the SD model, labor income is derived by multiplying GDP construction and labor income share. Labor income share is the percentage of GDP construction allocated to pay labor compensation.

To introduce the effect of inflation to the SD model, the CPI was used to depict how changes in the state of the economy impact labor wages. The CPI measures the relative price changes of a basket of goods and services over 2 consecutive years (US Bureau of Labor Statistics 2021). It is one of the most widely used measures of inflation (Ashuri et al. 2012). It also adjusts for factors such as the cost of living and purchasing power. In this research, CPI was used to enable the model to simulate the effect of inflation rates and price changes on labor wages. It acts as a correction factor that accounts for changes in the national economy when calculating the adjusted labor income. Table 5 provides the equation followed to adjust the labor income variable in accordance with the nation's monthly CPI data.

Afterward, the adjusted yearly wage was derived from labor income. The adjusted yearly wage is the average yearly labor income received by a construction worker excluding benefits and services such as health insurance. It is worth noting that the adjusted yearly wage is different from the average yearly wage parameter mentioned in the previous subsection. The average yearly wage, in the industry characteristics system, is retrieved directly from data reported by the US Bureau of Labor Statistics. However, the adjusted yearly wage is calculated based on labor income, supply–demand ratio, and labor income share. According to labor economics, a higher labor income share accompanied by increasing real wages tends to be expansionary. On the other hand, an increase in the labor income share coinciding with a decrease in real wages results in lower GDP (Hur 2021). This is why it was important for the authors to include both variables and clarify the distinction between them.

According to the AGC, the average hourly earnings of construction workers increased by over 3.2% in 2019 (AGC 2019). This increase was more than 10% higher than the average wage of private-sector skilled workers in the US (Ford 2022). In addition to other reforms that construction companies are implementing to mitigate labor shortages, this pay increase was reported to be effective in attracting skilled workers into construction careers (AGC 2019). Although the pay pump played a major role in the workers' decisions to work in construction, it is believed that skilled labor also considered working in the industry because their wages would be higher than they would be in some other industries.

To model this relationship in the economic conditions system, the average yearly wage of both construction workers and all workers across the US were considered. It was assumed that the higher the average yearly wage of construction workers in comparison with that of the national average of all workers, the more attractive the career in construction becomes, and thus the higher the labor retention rate. The opposite is also true for the opposite case: the higher the national average wage of all workers in comparison with that of construction workers, the more likely construction workers are to consider jobs in alternative industries, and hence a lower labor retention rate. Accordingly, the higher the best alternative opportunity which is the average yearly wage all workers divided by the average yearly wage of construction workers, the higher the proportion of construction workers who would consider switching to other industries for better pay. Thus, the lower the labor retention rate will be in the SD model, and vice versa.

Stock-Flow Diagram

Components in the SD model can be categorized as stocks, flows, dynamic variables, and constant parameters. Stocks include the inventory of a population such as the number of skilled workers in the construction market. Thus, they represent the state of the system. Flows can either be inflows or outflows, and they are the rates of increase or decrease of the stocks. Hence, they represent the rate of change in the state of the system. Accordingly, the relation between stocks and flows in a system dynamics model is expressed by the following integral equation:

$$\text{Stock}\,(t) = \int_{t_0}^{t} [\text{Inflow}\,(s) - \text{Outflow}\,(s)]ds + \text{Stock}\,(t_0) \qquad (3)$$

where t_0 = initial time; t = current time; Stock (t) = value of stock at time t; Stock (t_0) = initial value of stock; Inflow (s) = rate of increase of the stock at any time between t_0 and t; and outflow (s) = rate of decrease of the stock at any time between t_0 and t. Inflow (s) and outflow (s) have the units of stock (t) divided by time. Dynamic variables are functions of stocks, other variables, and/or constants. Lastly, constant parameters are variables that witness changes during the simulation so minimal that they are considered constant. All these elements can be graphically represented by a stock-flow diagram. In this paper, the three systems (i.e., construction labor market, industry characteristics, and economic conditions) were represented by one stock-flow diagram. The model was implemented in AnyLogic 8.7.9, where the mathematical equations and relationships between variables were modeled as described previously. Please refer to Fig. 2 for the stock and flow chart of the developed model.

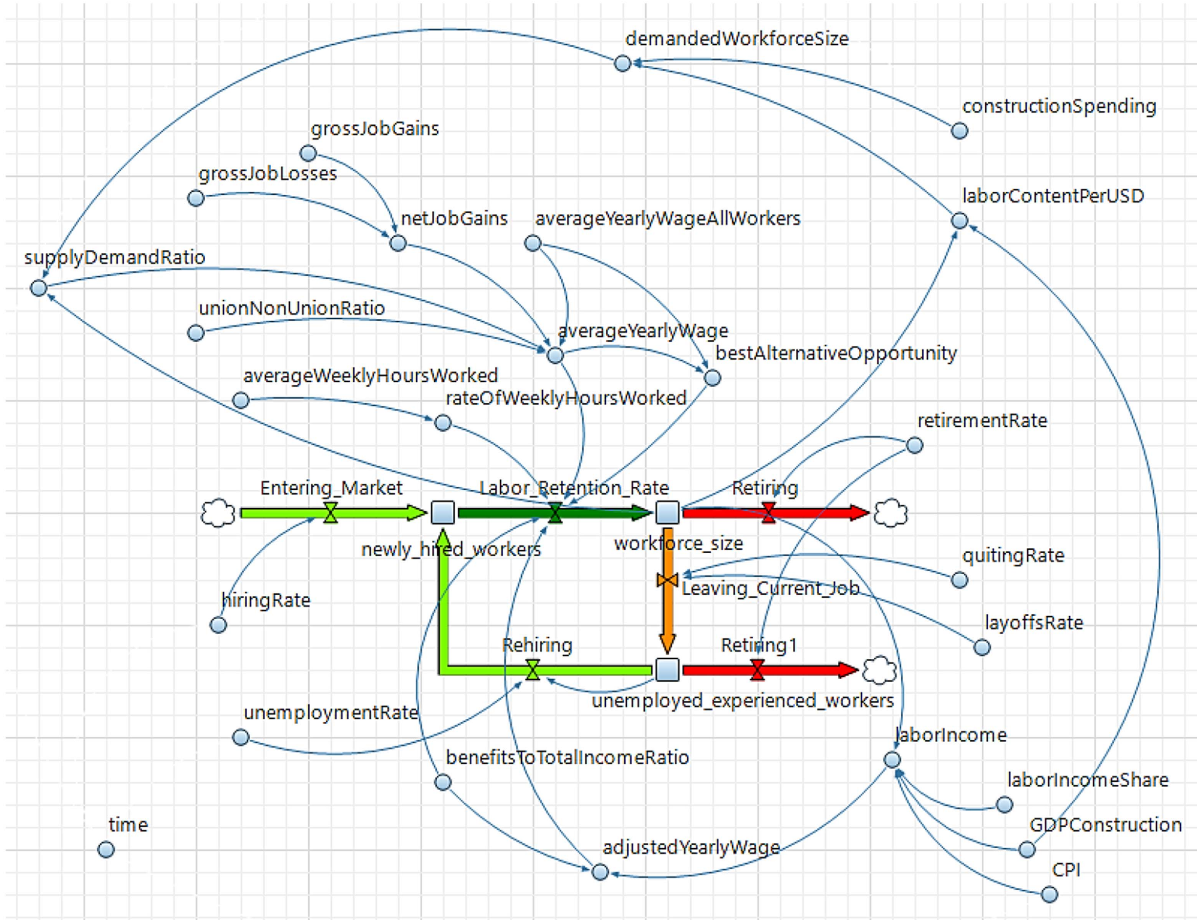

Fig. 2. Stock and flow diagram of the system dynamics model of the construction labor market.

Model Initializing and Simulation

After plotting the stock-flow diagram, data collection efforts commenced to serve two purposes: (1) set the initial values for the model's parameters and stocks, and (2) calibrate the model. Three types of data were needed: data for the stocks in the construction labor market system, data for the parameters of the industry characteristics system, and data for the variables in the economic conditions system. In this paper, various sources were used for data collection, including the US Bureau of Labor Statistics, US Bureau of Economic Analysis, and other data analytics firms.

In this paper, the model was not designed to make future predictions about variables such as hiring rate and unemployment rate. Instead, these factors are input variables that were modeled based on historical data to provide a realistic representation of past trends and their impact on workforce size and retention rate. As such, the model was trained using monthly reported data relevant to the US on the country level for a period of 18 years from 2004 to 2021. However, it can also be trained using other sets of data such as state- or city-level data, so it would be able to provide state-/city-related findings. The initial values of the parameters and stocks in the construction labor market, industry characteristics, and economic conditions systems are provided in Table 6.

SD Model Validation

Model validation is an important process that aims at confirming the soundness and usefulness of a system dynamics model (Ogunlana et al. 2003). In this paper, the SD model was evaluated using structural validation, as well as behavioral validation and calibration tests.

Structural Validation

The structural validity of the SD model was evaluated using the dimensional consistency test. The purpose of this test is to verify that the equations that define the hard relationships in the SD model are mathematically consistent and have real-world meaning (Ng et al. 2007). The dimensional consistency test was performed by assessing that the units of measure of variables on both sides of an equation were consistent (Gerami Seresht and Fayek 2018). As such, all equations governing hard relationships established in this research (Tables 3–5) were examined. For example, in Eq. (1), the unit of measure of the variable on the left-hand side is $\left(\frac{\text{number of workers}}{\text{months}}\right)$, which conforms with the units of measure of the variables on the right. Accordingly, Eq. (1) is deemed to be dimensionally consistent.

Behavioral Validation and Calibration

Behavioral validation and calibration tests assess the performance of a model by determining whether it can imitate the behavior of a real-world system and provide accurate evaluations of system outputs (Seresht and Fayek 2020). In the study, the developed SD model was evaluated using (1) pattern verification tests, and (2) prediction accuracy tests. The pattern verification test entails comparing the trends of the actual data sets retrieved from the appropriate data sources with those provided by the SD model over the simulation time. In other words, the process is like an optimization problem where the system parameters are adjusted to minimize the difference between the historic performance of the real data over time and the output of the model over the same period using prediction

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Table 6. Simulation values for the system dynamics model

System	Element name	Initial value	Description/source
Construction labor market	Education and training	932.94 (in thousands)	Retrieved from Steinberg and Nadworny (2022)
	Newly hired workers	6,121 (in thousands)	Retrieved from the employment levels for production and nonsupervisory employees in the construction industry data set published by the US Bureau of Labor Statistics.
	Workforce size	5,193 (in thousands)	Retrieved from the employment levels for production and nonsupervisory employees in the construction industry data set published by the US Bureau of Labor Statistics.
	Unemployed experienced workers	176.5 (in thousands)	Retrieved from the employment levels for production and nonsupervisory employees in the construction industry data set published by the US Bureau of Labor Statistics.
Industry characteristics	Hiring rate	Table function of monthly data points from 2004 to 2021	Calculated based on the number of hires divided by the employment levels in the construction industry. Both number of hires and employment levels were retrieved from the construction industry data set published by the US Bureau of Labor Statistics.
	Unemployment rate	Table function of monthly data points from 2004 to 2021	Retrieved from the construction industry data set published by the US Bureau of Labor Statistics.
	Gross job gains	Table function of monthly data points from 2004 to 2021	Retrieved from the construction industry data set published by the US Bureau of Labor Statistics.
	Gross job losses	Table function of monthly data points from 2004 to 2021	Retrieved from the construction industry data set published by the US Bureau of Labor Statistics.
	Union–nonunion ratio	Table function of monthly data points from 2004 to 2021	Retrieved from the construction industry data set published by the US Bureau of Labor Statistics.
	Construction spending	Table function of monthly data points from 2004 to 2021	Retrieved from the construction industry data set published by the Federal Reserve Economic Data online database.
	Benefits to total income ratio	Table function of monthly data points from 2004 to 2021	Retrieved from the construction industry data set published by the US Bureau of Labor Statistics.
	Retirement rate	Table function of monthly data points from 2004 to 2021	Retrieved from the construction industry data set published by the US Bureau of Labor Statistics (Toossi and Torpey 2017).
	Quitting rate	A table function of monthly data points from 2004 to 2021	Retrieved from the construction industry data set published by the US Bureau of Labor Statistics.
	Layoffs rate	A table function of monthly data points from 2004 to 2021	Retrieved from the construction industry data set published by the US Bureau of Labor Statistics.
	Average weekly hours worked	A table function of monthly data points from 2004 to 2021	Retrieved from the construction industry data set published by the US Bureau of Labor Statistics.
Economic conditions	GDP construction	A table function of monthly data points from 2004 to 2021	Retrieved from the US Bureau of Economic Analysis.
	Labor income share	A table function of monthly data points from 2004 to 2021	Retrieved from the construction industry data set published by the US Bureau of Labor Statistics.
	CPI	A table function of monthly data points from 2004 to 2021	Retrieved from the CPI for urban consumers data set published by the US Bureau of Labor Statistics.
	Average yearly wage all workers	A table function of monthly data points from 2004 to 2021	Retrieved from the US Bureau of Economic Analysis.

accuracy tests (Abotaleb and El-adaway 2018). This is essential to ensure that the model can imitate the key features of the patterns generated by the actual data. Such key features include increasing and decreasing trends, local and global maximum and minimum points, and frequency of cyclic data waves.

Single-stage calibrations are the norm for SD models that are composed of a single module (i.e., the case herein) but more sophisticated multistage calibration processes are advised for SD models that incorporate various interacting modules (Abotaleb and El-adaway 2018). To this end, the behavior of the model was verified by comparing the results of the simulation of the SD model with actual data points. The accuracy of the results of the model can be assessed using different error metrics such as root-mean square error (RMSE) as illustrated in Eq. (4) that can be better interpreted using normalized root-mean square error (NRMSE) by dividing the RMSE by the difference between the maximum and minimum values, or mean absolute percentage error (MAPE) as illustrated in Eq. (5). As rules of thumb, NRMSE and MAPE scores of 30% or below should suffice to confirm a reasonable validity of the model and confidence in its results (Seresht and Fayek 2020)

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(\text{simulation result}_i - \text{actual data}_i)^2}{N}} \tag{4}$$

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\text{actual data}_i - \text{simulation result}_i}{\text{actual data}_i}\right| \tag{5}$$

Sensitivity Analysis

Sensitivity analysis is the process of identifying a set of model inputs, then analyzing how variations in such inputs impact the magnitude of model outputs (Chen et al. 2019). The purposes of sensitivity analysis are to identify the factors that have the most influence on model output, identify the scale to which, if any, such factors interact with each other, and identify regions in the space of inputs where the variation in model output is maximum/minimum (Hall et al. 2009). Further, it is used to attain a more thorough examination of the characteristics and patterns of behaviors of the model parameters (Jiang et al. 2015).

In this research, the developed SD model was used as a base for conducting sensitivity analysis to further explore the issue of skilled labor shortage. As such, a univariate sensitivity analysis was

Table 7. Run number and corresponding percent change of experimental variable

Experimental variables	Percent change of experimental variable −80%	−60%	−40%	−20%	20%	40%	60%	80%
Hiring rate	R01	R02	R03	R04	R05	R06	R07	R08
Union–nonunion ratio	R09	R10	R11	R12	R13	R14	R15	R16
Construction spending	R17	R18	R19	R20	R21	R22	R23	R24
Benefits to income ratio	R25	R26	R27	R28	R29	R30	R31	R32
Average yearly wage	R33	R34	R35	R36	R37	R38	R39	R40
Labor income share	R41	R42	R43	R44	R45	R46	R47	R48
CPI	R49	R50	R51	R52	R53	R54	R55	R56
Average yearly wage all workers	R57	R58	R59	R60	R61	R62	R63	R64

conducted to study how variations in a set of input variables affected the model outputs. Eight input variables from both the industry characteristics and economic conditions systems were taken as experimental variables. An experimental variable is an independent variable that is manipulated to determine its relationship to, or influence upon, an outcome or a dependent variable. In this study, the selected experimental variables were hiring rate, union–nonunion ratio, construction spending, benefits to total income ratio, average yearly wage, labor income share, CPI, and average yearly wage all workers.

The authors opted to prioritize these variables as experimental variables for the sensitivity analysis above the rest of the input variables for a number of reasons. First, according to the information detailed in the "Background" section, these variables are expected to have the greatest impact on the output of the model (Cheng et al. 2017). Second, these are typically the parameters that are most likely to be affected by changes in external factors (Chakraborty and Chowdhury 2017). Third, and most importantly, these factors are all relevant to some of the ongoing issues in the construction sector. For example, several sources have attested to the strong correlation between the hiring rate and construction spending in the construction industry on one hand and shortages of skilled workers on the other (Abbaspour and Dabirian 2019; AGC 2018; Ashtab and Ryoo 2022).

For each experimental variable, eight runs were performed, where each run constitutes an increment of change from the original data series used in the base run. Meanwhile, the remainder of the model's input variables are held constant. Ultimately, a total of 64 runs were conducted using the model. Table 7 better illustrates the total number of runs performed and the corresponding percentage change of experimental variables. For example, Run 21 (R21) assumed a 20 % increase of the experimental variable construction spending across all the construction spending data points collected over the period from 2004 to 2021. However, the rest of the experimental variables all remained constant.

The model outputs are the workforce size and labor retention rate of skilled labor in the construction market. Their sensitivity was analyzed for each scenario and compared with the base run simulation to provide a beneficial reference for mitigating labor shortages in the construction market. It is worthy to note that the SD model developed in this research can simulate various scenarios regarding each of the model variables. However, this analysis focused primarily on a set of configurations aimed at examining the issue of skilled labor shortage.

Results and Analysis

This section presents the results and analysis of this paper in relation to (1) the developed SD model; (2) simulation of the SD model; (3) model validation, including behavior, calibration, and pattern verification; and (4) sensitivity analysis.

Developed SD Model

Fig. 2 presents the developed SD model. As detailed in the "Methodology" section, the model consists of three main systems: (1) construction labor market, (2) industry characteristics, and (3) key economic conditions.

Simulation Results

The simulation conducted in this study represents the behavior of the skilled construction labor market system over a time period of 18 years from 2004 to 2021, with monthly time steps. Meaning, the simulation was run for a total of 216 time steps. The graphs in Fig. 3 were obtained upon running the simulation, and thus they demonstrate the results of the developed SD model. The figure includes graphs for the two main variables assessed in this study (skilled labor workforce size and labor retention rate), in addition to a number of other variables that serve to provide a better understanding of the model. Fig. 3(a) shows the cumulative number of newly hired skilled labor, the number of skilled labor currently involved in the workforce, and the demanded labor at each time step of the simulation (month). Fig. 3(b) visualizes the number of experienced skilled workers who quit their jobs or got laid off by their employers. Lastly, Fig. 3(c) illustrates the rate of retention of skilled labor in the construction market as calculated monthly by the model for the period from 2004 to 2021.

The simulation results in Fig. 3(a) show the following: the number of skilled labor workers in construction remained relatively stable over the entire simulation period, with only minor fluctuations occurring consistently throughout the time frame. Initially, during the first 50 months of the simulation (mid-2000s), there was a slight increase in the number of skilled workers. This was followed by a period of steady decrease that lasted for approximately 50 months (from 2008 until 2016). However, starting from around Time step 200, the number of skilled labor workers gradually increased again. From that point until the end of the simulation, there was a downward trend, which coincided with the period between 2020 and 2021, during which the impact of the COVID-19 pandemic on the construction industry was evident by the decline in the number of skilled workers.

Labor demand, which is the number of demanded labor at each time step, experienced a trend similar to that of skilled labor workforce size. However, the fluctuations between the highest and lowest points were more significant. This indicates that the industry characteristics and economic conditions considered in the SD model have a similar impact on both skilled labor workforce size and labor demand. However, labor demand was relatively more sensitive to such variables in comparison with labor supply. As for the skilled

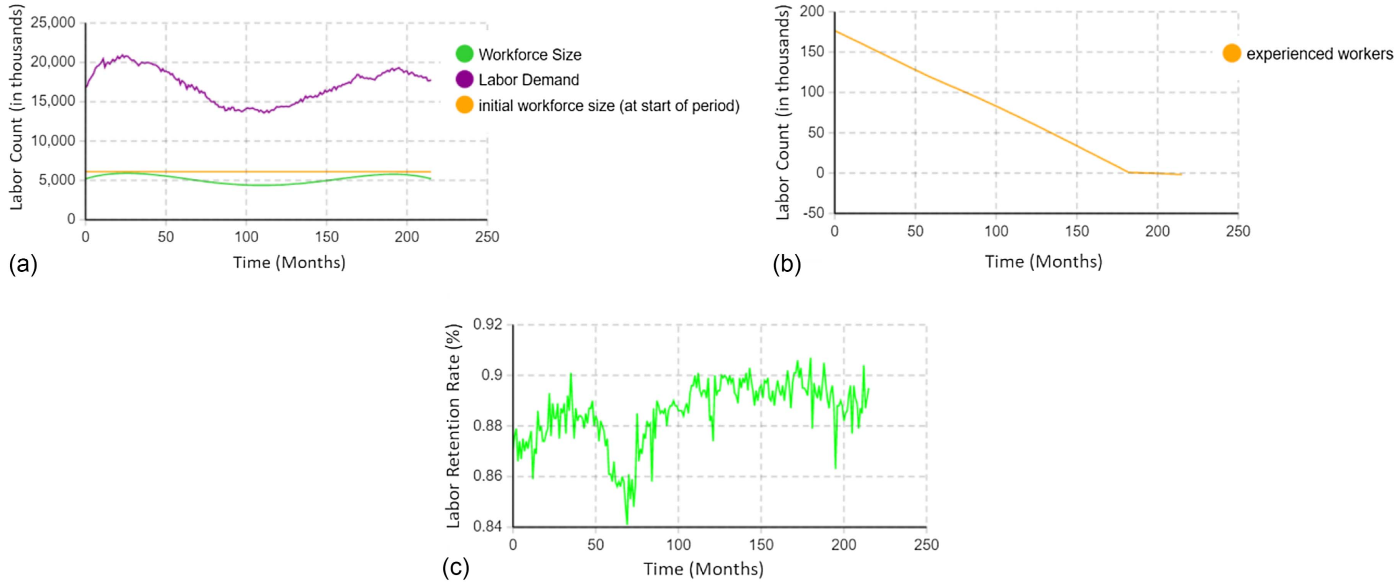


Fig. 3. Simulation results of the SD model: (a) workforce size, labor demand, and newly hired workers over time; (b) experienced workers over time; and (c) labor retention rate over time.

workers newly entering the construction market, their count was constant across the simulation period. Also, according to the model results demonstrated in Fig. 3(b), the pool of experienced skilled workers who get laid off or decide to leave their jobs decreased by less than 1% each year. Such findings confirm the stability of the construction market in terms of the reduced probability of a worker quitting or being fired (Kim and Philips 2012). It also highlights the industry's keenness to rehire experienced skilled workers once available and willing to continue working in the construction sector.

Lastly, Fig. 3(c) shows that the retention rate of labor demonstrated an overall upward trend during the initial 50 months of the simulation period (2004 to 2008). Afterward, there was a decrease for around 40 months. This decline coincided with the global financial crisis of 2008, which had significant impacts on the construction industry and subsequently the labor market for construction workers (Castelblanco et al. 2022). Around Time step 90 (the year 2011), the retention rate began to rise again, eventually stabilizing at a new high that exceeded the precrisis level. However, there was another less significant decrease in the retention rate during the months from Time steps 195 to 202 (the year 2020) due to COVID-19, followed by a subsequent increase until the end of the simulation period. Nevertheless, the retention rate remained lower than prepandemic levels.

Model Validation

In this paper, the behavior validity of the SD model was evaluated by running the model for its entire simulation period, then comparing the results provided by the model with actual data. As mentioned previously, the simulation covered 216 data points that represent monthly time steps for the period from 2004 to 2021. Model outputs in relation to two variables were collected and compared with their corresponding actual data. These two variables are workforce size and labor retention rate. Figs. 4 and 5 present the actual data versus the simulation results provided by the SD model for both workforce size and labor retention rate variables. Fig. 4 presents the comparison results for the workforce size for the entire simulation period. Fig. 5 presents the same for the labor retention rate. The x-axis in Fig. 4 shows the time steps of the SD model measured

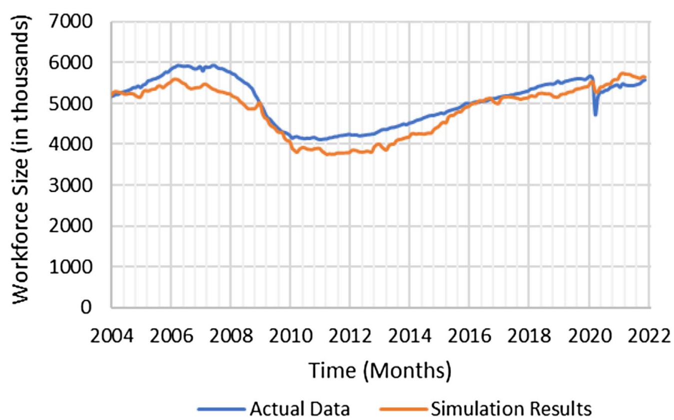


Fig. 4. Skilled labor workforce size: simulation results in comparison with actual data from US Bureau of Labor Statistics (BLS).

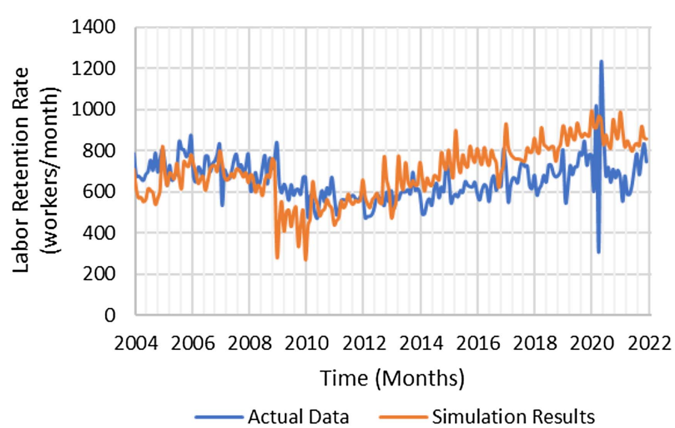


Fig. 5. Skilled labor retention rate: simulation results in comparison with actual data from BLS.

in months, and the y-axis shows the count of the construction skilled labor workforce size in thousands. Similarly, the x-axis in Fig. 5 is the time steps in months, and the y-axis is the labor retention rate presented as a ratio.

Using the pattern verification test to behaviorally validate the model, the trends depicted from the actual data are consistent with those generated by the model for skilled labor workforce size and the labor retention rate in most of the cases. It can be seen in Fig. 4 that the trends in the actual data collected from the Bureau of Labor Statistics (US Bureau of Labor Statistics 2021) for the workforce size were simulated correctly by the results obtained from the model for the majority of the data points. Also, Fig. 5 highlights that the fluctuations in the actual data related to labor retention rate were closely depicted by the pattern of the results obtained from the model throughout the entire period of the simulation.

In addition to similar visual trends, it is still important to assess the behavior validity and calibrate the developed SD model using the prediction accuracy test (i.e., RMSE, NRMSE, and MAPE) as previously mentioned in Eqs. (4) and (5) and referenced by Seresht and Fayek (2020) as well as Abotaleb and El-adaway (2018). To this end, for the workforce size variable, the RMSE was 313.39, with NRMSE of 0.061 (i.e., 6.1%). Furthermore, the MAPE was 0.054 (i.e., 5.4%). Finally, the RMSE for the labor retention rate variable was 143.55, with NRMSE of 0.218 (i.e., 21.8%). The MAPE was 0.176 (i.e., 17.6%). To this end, the collective results of RMSE, NRMSE, and MAPE for workforce size and labor retention rate variables confirm the validity of the model, thus proving its reliability in examining different behavioral scenarios.

Sensitivity Analysis

For each experimental variable, the sensitivity analysis runs were conducted using the developed SD model. Model outputs workforce size and labor retention rate were recorded for each run. Tables 8 and 9 provide the percent change in the workforce size and labor retention rate, respectively, for all performed simulations. The percentage changes were calculated with respect to the values obtained from the base run.

Generally, the simulation results show that the outputs of the SD model (i.e., workforce size and labor retention rate) were sensitive to all the tested experimental variables but to varying degrees. However, the workforce size was more responsive to variations in the experimental variables in comparison with the labor retention rate. Figs. 6–13 present the sensitivity analysis results graphically for each experimental variable.

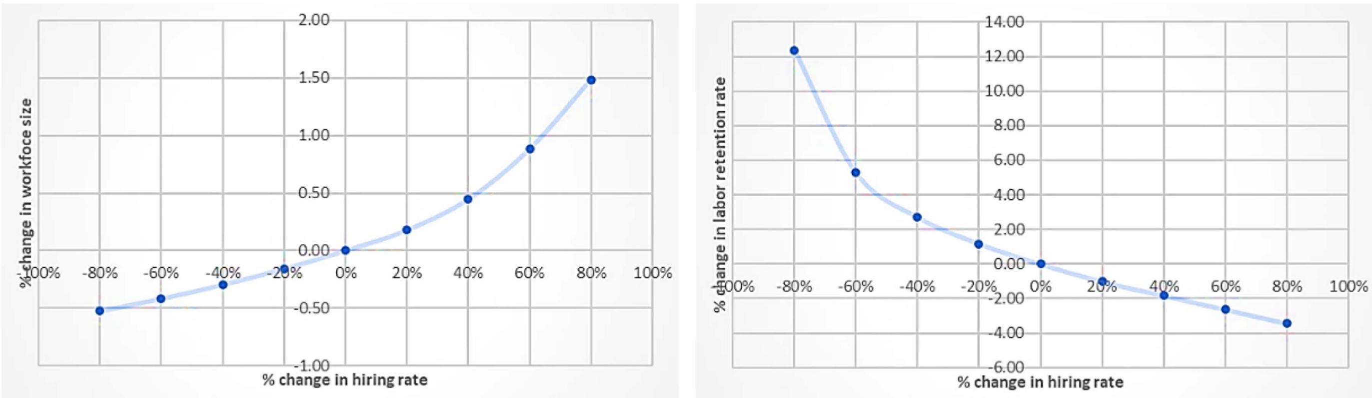
Figs. 6–13 indicate that all scenarios were successful in improving the conditions of the skilled labor market by increasing the workforce size and labor retention rate compared with the base run. The only exception to this was the hiring rate. As can be seen in Fig. 6, increasing the hiring rate had a positive effect on the workforce size. However, the labor retention rate was deteriorating as the hiring rate increased. Further, the results show that labor income share exhibited the best performance out of the eight experimental variables in terms of its impact on workforce size and labor retention rate. It can be seen in Fig. 11 that with each additional increment of labor income share, a substantial positive response was attained in both labor retention rate and workforce size. Likewise, a decreasing labor income share led to a decline in the labor retention rate and workforce size. In addition to labor income share, CPI had a considerable impact on workforce size and labor retention rate. However, as can be seen in Fig. 12, the effect of CPI on both outputs was not as linear as that of labor income share. This was evident especially in the runs where the percentage change in CPI exceeded −40%.

Table 8. Percentage change in workforce size for each experimental variable in each simulation run

	Experimental variable							
Percent change	Hiring rate	Union–nonunion ratio	Construction spending (thousands)	Benefits to income ratio	Average yearly wage	Labor income share	CPI	Average yearly wage all workers
−80	−0.524	−0.833	−28.582	19.195	−47.401	−78.524	391.604	−2.350
−60	−0.417	−0.622	−7.443	14.836	−26.513	−59.130	147.979	−2.586
−40	−0.295	−0.413	−3.048	10.203	−14.464	−39.569	65.943	−1.942
−20	−0.157	−0.206	−1.103	5.267	−6.241	−19.836	24.762	−1.034
Base run(0)	0	0	0	0	0	0	0	0
20	0.178	0.204	0.711	−5.635	5.105	19.813	−16.530	1.114
40	0.445	0.407	1.209	−11.676	9.512	39.600	−28.315	2.287
60	0.881	0.608	1.576	−18.171	13.471	59.361	−37.112	3.511
80	1.484	0.808	1.858	−25.167	17.136	79.098	−43.931	4.780

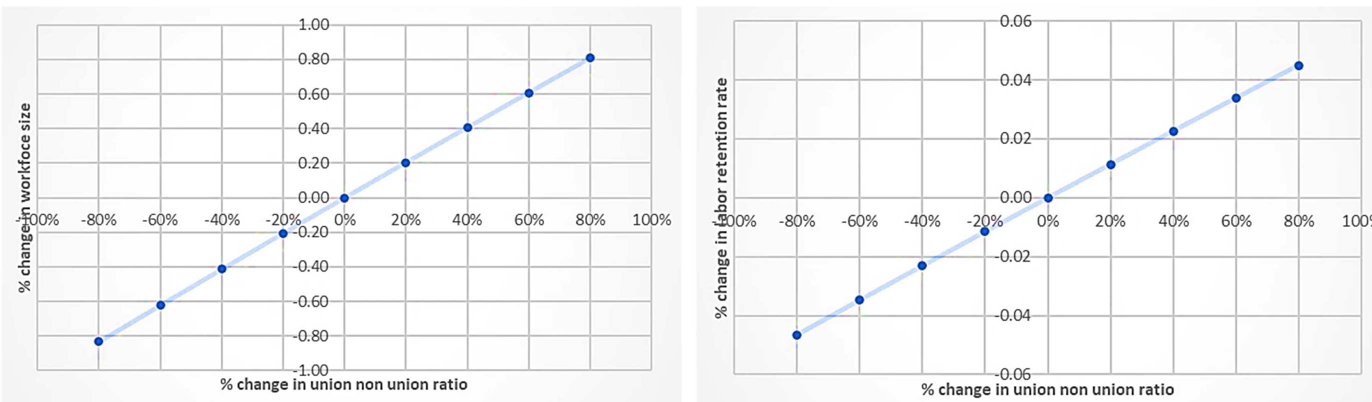
Table 9. Percentage change in labor retention rate for each experimental variable in each simulation run

	Experimental variable							
Percent change	Hiring rate	Union–nonunion ratio	Construction spending (thousands)	Benefits to income ratio	Average yearly wage	Labor income share	CPI	Average yearly wage all workers
−8	12.363	−0.046	−1.454	0.924	−2.899	−3.306	22.499	−0.207
−60	5.275	−0.035	−0.488	0.708	−1.616	−2.530	8.237	−0.197
−40	2.703	−0.023	−0.195	0.483	−0.985	−1.729	3.592	−0.142
−20	1.172	−0.011	−0.070	0.247	−0.412	−0.962	1.328	−0.075
Base run (0)	0	0	0	0	0	0	0	0
20	−1.022	0.011	0.045	−0.260	0.327	1.060	−0.868	0.079
40	−1.820	0.023	0.076	−0.535	0.605	2.136	−1.291	0.161
60	−2.630	0.034	0.099	−0.827	0.851	3.226	−1.641	0.246
80	−3.430	0.045	0.116	−1.046	1.078	4.326	−1.961	0.334



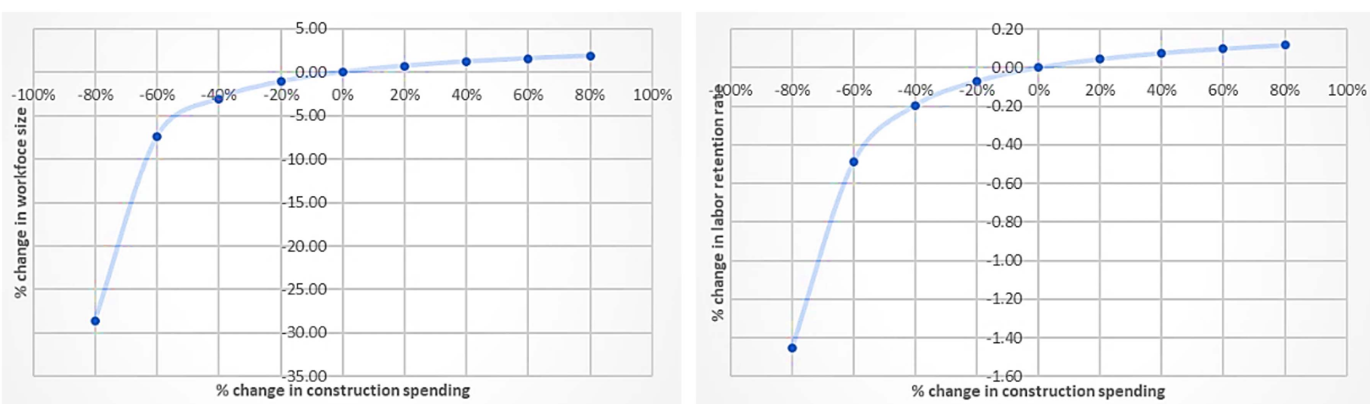
(a) (b)

Fig. 6. Effect of varying hiring rates on (a) workforce size; and (b) labor retention rate.



(a) (b)

Fig. 7. Effect of varying union–nonunion ratios on (a) workforce size; and (b) labor retention rate.



(a) (b)

Fig. 8. Effect of varying construction spending levels on (a) workforce size; and (b) labor retention rate.

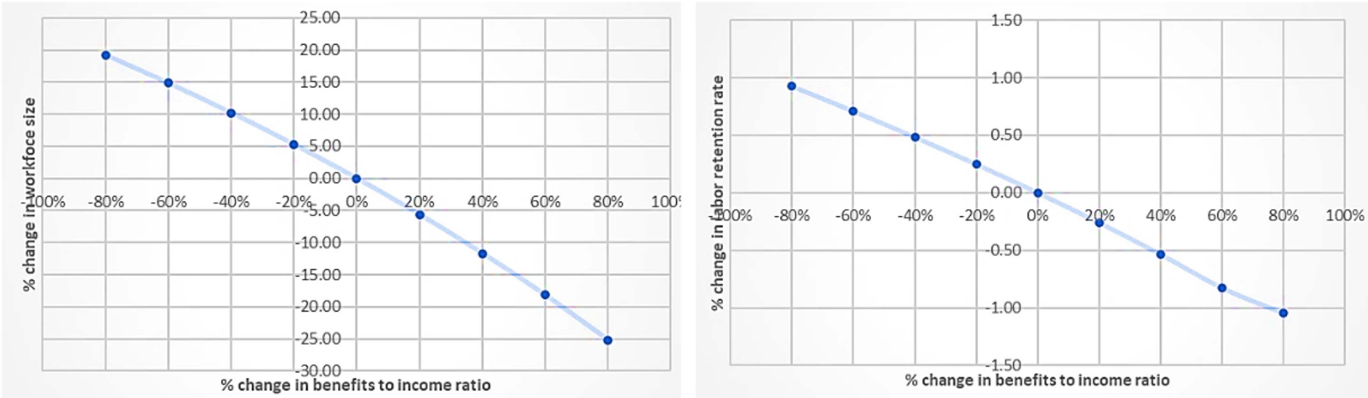
Discussion

Based on the results of this model, the workforce size and labor retention rate were found to be sensitive to all the experimental variables tested, but to varying degrees. However, the variables related to the economic conditions system had a relatively more significant impact on the model's outputs than those related to the industry characteristics system. This suggests that economic factors are more effective in attracting and retaining skilled labor to the construction industry. The following subsections discuss the key experimental variables examined in the sensitivity analysis from both the construction industry characteristics and the economic conditions systems of the SD model.

Construction Industry Characteristics

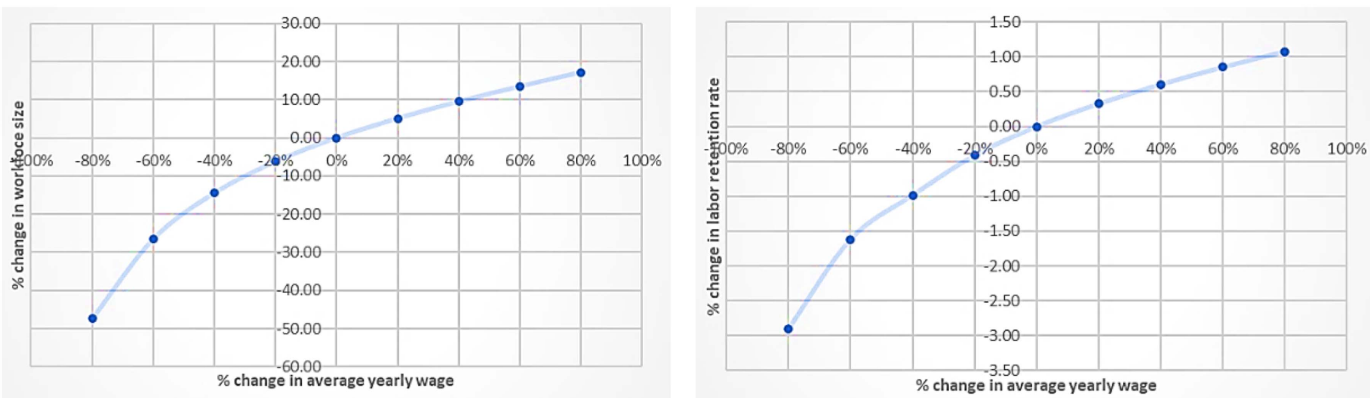
Hiring Rate

Findings showed that all positive changes introduced through the sensitivity analysis were effective in enhancing the conditions of



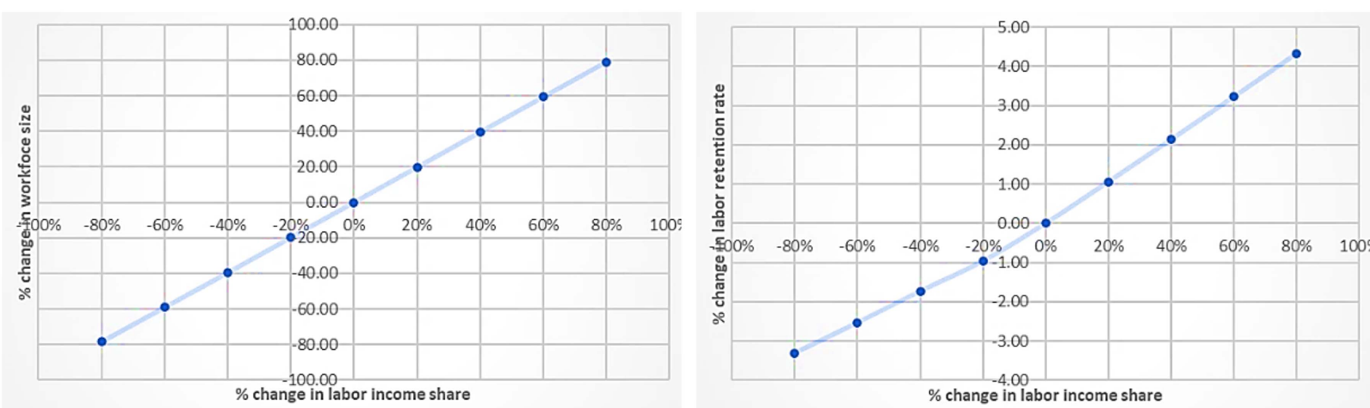
(a) (b)

Fig. 9. Effect of varying benefits to income ratios on (a) workforce size; and (b) labor retention rate.



(a) (b)

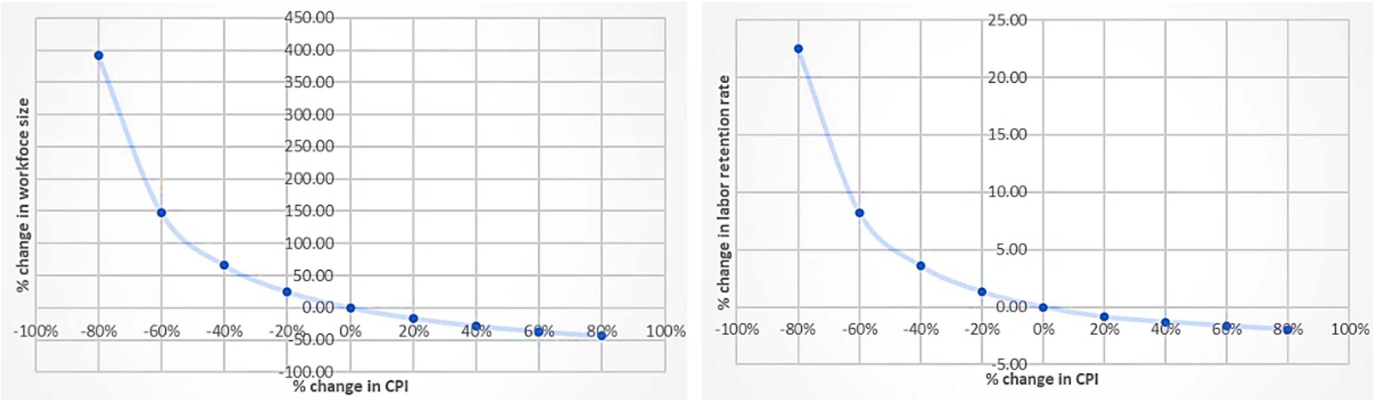
Fig. 10. Effect of varying average yearly wage levels on (a) workforce size; and (b) labor retention rate.



(a) (b)

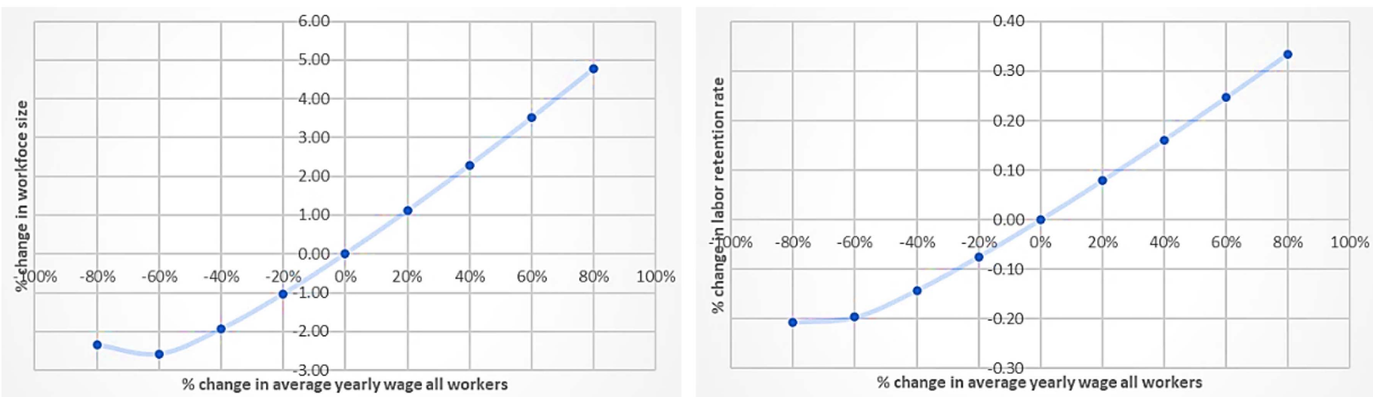
Fig. 11. Effect of varying labor income share ratios on (a) workforce size; and (b) labor retention rate.

the skilled labor market by increasing the size of the workforce and improving the rate of labor retention compared with the base run. The only exception to the latter was the hiring rate. Increasing the hiring rate had a favorable impact on the workforce size. However, the labor retention rate declined as the hiring rate increased. This can be attributed to two reasons. First, when holding the hiring rate as the experimental variable, the remainder of the model's variables typically remained equal to the values retrieved from the actual data. Accordingly, the negative influences of such variables would still be able to impact the model outputs. In this case, it can be suggested that increasing the hiring rate alone is not sufficient to offset the negative impacts projected by the rest of the variables. As such, the



(a) (b)

Fig. 12. Effect of varying CPI ratios on (a) workforce size; and (b) labor retention rate.



(a) (b)

Fig. 13. Effect of varying average yearly wage all workers levels on (a) workforce size; and (b) labor retention rate.

declining trajectory of the labor retention rate witnessed in the base run simulation would still be recognized.

According to Welfare et al. (2021), when construction companies are in a rush to employ workers to fill increasing demands for labor, workers may not be screened properly for adequate skills. This results in hiring unqualified candidates, which can backfire by forcing skilled labor, who are typically more costly, out of the industry and thus a declining retention rate of skilled labor. In addition, according to the logic implemented in the SD model, increasing the hiring rate increases the labor supply, and thus bridges the gap between labor supply and demand. Based on the law of demand, increasing the supply of skilled labor in the market without a corresponding increase in demand negatively impacts labor wages. According to del Rio-Chanona et al. (2020), low-income wages are highly susceptible to supply–demand changes compared with high-income occupations. Eventually, declining wages lead to deteriorating labor retention rates.

Construction Spending

The workforce size and labor retention rate experienced a dramatic decline when the change in construction spending dropped below −40% (Fig. 8). As previously discussed, construction spending was used in this model as a measure of labor demand. Therefore, when construction spending decreased to the point at which labor supply surpassed demand, construction workers' average yearly wage decreased, and the best alternative opportunity metric increased. These two trends combined led to the plunging of the labor retention rate as well as the number of skilled labor in the construction workforce. This is further corroborated by the findings of Ashtab and Ryoo (2022), which identified a strong relationship between national-level construction spending and the construction market (specifically hiring level and hourly wages).

Average Yearly Wage

The average yearly wage witnessed a pattern similar to that of construction spending. The workforce size and labor retention rate declined at a steeper rate after the percent change in the average wage of construction workers exceeded −20% (Fig. 10). This is because at the −20% point, the average wage of construction workers became lower than the average wage of all workers. Accordingly, construction workers would be motivated to pursue alternative job opportunities in other industries, thus increasing the value of the best alternative opportunity (del Rio-Chanona et al. 2020). Ultimately, this would result in a declining supply of skilled construction labor as demonstrated by the decreasing labor retention rate and workforce size.

Union–Nonunion Ratio

Findings show that the union–nonunion ratio had minimal effect on the conditions of the construction labor market. Even though the median weekly wage of a union worker is more than 30%

higher than that of a nonunion member in construction (Phillips 2022), the number of union members remains relatively limited in the construction industry, with only 13% of US workers being union members in 2021 (US Bureau of Labor Statistics 2021). This explains the weak association between union–nonunion ratios and construction labor market conditions.

Economic Conditions

Labor Income Share

As mentioned previously, labor income share had the most significant impact on the workforce size and labor retention rate. Increasing the labor income share led to a substantial positive response in both model outputs (i.e., retention rate and workforce size). When holding constant other model inputs such as CPI, which represents the inflation rate, it was found that increasing the share of the construction industry's GDP dedicated to construction labor led to an equally proportional increase in labor income. Such an increase was further reflected in the adjusted labor wage, which is the inflation-adjusted labor wage excluding benefits and services. Subsequently, this led to a higher rate of skilled labor retention, which over time resulted in the aggregation of more skilled workers in the construction market. This is in line with what Manning (2021) mentioned. A falling labor share in national income is associated with difficulties in the recruitment and retention of workers.

Adjusted Labor Wage

Although both adjusted labor wage and average yearly wage measure the effect of labor wages on the supply of skilled workers in the market, a comparative examination of the two factors showed that adjusted labor wage had a significantly higher impact on both labor retention rate and workforce size across all simulation runs (Figs. 10 and 11). In this paper, the adjusted labor wage, also known as real income in economic domains, was assumed to be the average yearly wage after subtracting the economic inflation rate per USD for all income dollars. Therefore, it has a lower value and a decreased spending power compared with the average yearly wage.

As such, the adjusted labor wage measures an individual's actual purchasing power in an open economy after accounting for inflation. Therefore, raising or reducing it has a much more direct impact on the ability of workers to afford living costs and thus their decision to remain in the industry or switch to a higher-paying job in another field. To that end, it can be deduced that the ongoing efforts to increase labor wages as captured from the data by the Bureau of Labor Statistics (refer to the base run) are not sufficient to ensure the continued involvement of skilled labor in construction. Instead, a more promising solution to retain skilled labor in construction would be to increase the percentage of pay raises beyond that of the inflation rate. According to economic reports, labor wages are rising, but they are not keeping up with inflation (Furman and Powell 2022). Two-thirds of workers in the US said their pay is not keeping up with these higher prices. As such, construction companies are experiencing increased difficulties in retaining workers (Lorsch 2022).

Contributions to the Body of Knowledge and Practical Implications

This study is the first known attempt to create a simulation model that combines economic indicators and industry characteristics to address the issue of skilled labor shortage in the construction market. Through the use of SD modeling, this research sheds light on the complex and interconnected relationships between economic conditions, industry factors, and the retention of skilled workers in construction. It also provides a much-needed approach to understanding their dynamic nature and collective impact on the construction labor market. Furthermore, by conducting sensitivity analysis using the developed SD model, the authors were able to identify key economic and industry factors that influence skilled labor retention. Such factors include the hiring rate, average yearly wage, labor income share, and CPI. Further, findings showed that economic indicators had a more impactful influence on labor retention patterns compared with industry characteristics. This suggests that reforms associated with economic factors such as labor income share and CPI can be more effective in increasing the size of the skilled labor workforce and labor retention rates.

Moreover, the methodological approach and modeling framework developed in this research is transferable to other economies. The latter is possible given the availability of the needed data in other countries. For example, the model in this paper was trained using country-level data from the US. However, it can also be trained using other sets of data from different countries, so it would be able to provide country-related findings. Ultimately, the developed model offers industry practitioners, governmental agencies, and other associated stakeholders a useful tool to test various scenarios including national-level economic policies and labor retention regulations that affect the construction skilled labor market. Consequently, this allows users to analyze the impact of variables such as fiscal policies, economic support plans, and construction spending strategies.

Limitations and Future Work

This section presents the limitations of the developed model that need to be addressed in future research. One limitation of the model is that some of the parameters have several alternatives for calculating them. To this end, and where the authors opted to use the equations aforementioned in this study in accordance to the reviewed literature, the validation efforts, as well as the sensitivity analysis, might be different if other equations were to be used. However, because the authors managed to properly develop and assess the model under the current equations, they should be able to do the same under another set. As such, this limitation does not impact the reliability of the developed model beforehand.

Another limitation is that complete sets of data are not always available. This led to two constraints. First, the simulation of the model was limited to 18 years from 2004 to 2021. Second, some factors that the authors believe would have been important to include in the model were not added due to the lack of real-world data. Such factors include technology level and workers contract type. Moreover, the model presented in this paper focused on factors that impact the retention of skilled labor within the industry. However, it is the authors' view that factors that affect the entry of skilled labor into the construction market are equally important and should be considered in future work. If this is to be the case, the SD model will involve multiple modules and will most likely need to be calibrated using a multistage process. All these limitations can be considered in future research efforts.

Conclusion

This research investigated the impact of key construction industry characteristics and economic indicators on the retention of skilled workers in the construction labor market using the SD approach. To achieve that, a literature review was conducted to identify factors influencing the shortage of skilled labor in construction. The authors were able to identify 17 industry-level construction characteristics and seven national-level macroeconomic indicators that influence the conditions of skilled workers in the construction labor market. Furthermore, a SD model that consists of three systems [i.e. (1) construction labor market, (2) industry characteristics, and (3) key economic conditions] was developed.

Then, country-level data were collected to set the initial values for the model's parameters and calibrate the model. A dimensional consistency test was used to ensure the structural validity of the SD model. For behavioral validation, pattern verification and prediction accuracy tests were conducted to evaluate the performance of the model. Lastly, a univariate sensitivity analysis was conducted to study how variations in a set of experimental variables affected the model outputs. The experimental variables included hiring rate, union–nonunion ratio, construction spending, benefits to total income ratio, average yearly wage, labor income share", CPI, and average yearly wage all workers.

Results showed that the model outputs (i.e., workforce size and labor retention rate) were sensitive to all tested experimental variables to varying degrees. Still, economic indicators were found to have a more impactful influence on labor retention patterns compared with industry characteristics. This suggests that although a combination of both economic and industry related factors was the most effective strategy to enhance the conditions of the construction labor market, reforms associated with economic indexes such as labor income share and CPI can be more impactful in increasing the size of the skilled labor workforce and the labor retention rates.

In addition, the model was able to capture the impact of worldly events such as the financial crisis of 2008 and COVID-19 pandemic on the construction labor market. Overall, the model presented in this paper can be used as a basis to test various scenarios including high-level economic policies and labor retention regulations that affect the construction skilled labor market. It helps users to analyze the impact of variables such as fiscal policies, economic support plans, and construction spending strategies. This can provide useful insights to policymakers, economists, and business analysts for better-informed decision making.

Data Availability Statement

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

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