Survey-Based Data-Driven Dashboard for Planning Off-Site Construction Projects: Wall Framing Case Study

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Abstract

While accurate planning is fundamental to effective construction project management, existing planning tools remain insufficient to inform practitioners' decision-making in off-site construction (OSC) production facilities as they often rely on detailed historical data and company-specific data. Although surveys are commonly used to collect industry knowledge, most prior efforts have focused on on-site construction processes, and their findings have rarely been transformed into actionable planning-support strategies. This study addresses these gaps by proposing a survey-based, data-driven framework for developing an interactive planning dashboard tailored to OSC operations. The framework is structured into five phases: (1) defining the planning scope and influencing factors, (2) developing a survey questionnaire, (3) building an estimation model to predict operational duration, (4) designing a data pipeline that automates data flow between tools, and (5) implementing a Power BI dashboard for scenario-based analysis to support planning activities. Survey responses and model-predicted outcomes are continuously integrated into the dashboard, enabling users to compare planning scenarios, evaluate performance against industry data, and explore operational changes, such as automation upgrades or workforce adjustments. A pilot case study on wall framing demonstrates the applicability of the framework.

Keywords –
Off-site construction; planning; survey; dashboard; wall framing

1 Introduction

The construction industry has increasingly adopted OSC practices to transform traditional, site-based activities into controlled, factory-based production environments, thereby improving project performance, productivity, and predictability. By shifting construction activities to manufacturing facilities, OSC enables higher levels of standardization, process control, and repeatability compared to conventional on-site construction [1], [2]. However, realizing these benefits depends heavily on the availability of effective planning systems that support informed decision-making during production planning and scheduling [3]. Moreover, OSC practices can reach their full potential only when there is an equivalent level of demand for prefabrication, which may be possible given the federal Government's efforts toward industrialized construction. In the context of OSC, part of planning entails estimating production time, defined as the time required to manufacture a specific building component (e.g., wall panels, floors, or roof assemblies) within a factory setting. These production time estimates serve as critical inputs for developing production schedules, allocating resources, and evaluating operational performance [4] . The production time is influenced by a range of factors, including workforce characteristics, equipment and machinery, material handling, level of automation, production errors, and rework [5].

To estimate production durations in OSC, prior studies have leveraged a variety of analytical and computational tools. These include discrete-event simulation [6], optimization models [7], digital twin frameworks [4], machine learning algorithms [4], and sensor-based data acquisition systems [3]. Such approaches have demonstrated strong potential to capture complex production dynamics and improve the accuracy of duration estimation under specific operational conditions. In most cases, these studies rely on detailed input data collected through direct observations, time-motion studies, sensing technologies, captured images and videos, or historical production logs, and typically report outputs as predicted cycle times, production rates, or system-level performance indicators. Despite their technical rigor, a key limitation of existing OSC planning and duration estimation studies lies in their limited transferability. Most models are custom-developed and calibrated for a single case factory, production line, or component type, which restricts their immediate applicability to other OSC facilities with different layouts, technologies, or organizational structures. For example, if an estimation model was developed for semi-automated wall framing operations in OSC without a robotic arm, it might be easier to transfer the model to another factory with a similar level of automation than to one that incorporates a robotic arm to assist with stud placement, which would require modifications to the model. Moreover, many of these approaches depend on complex data acquisition systems and significant computational expertise, creating practical barriers for small- and medium-sized OSC companies or new market entrants with limited historical data and resources. As a result, there is a growing need for more generic, scalable, standardized, and industry-oriented planning tools that allow OSC companies to assess their operational performance and benchmark it against industry practices. Benchmarking-based approaches can enable companies to compare production durations, evaluate the impacts of automation or workforce changes, and identify performance gaps relative to peers operating under different production configurations [8]. Such tools are particularly valuable for companies seeking to upgrade their operations, for example, transitioning from manual to semi-automated production, as well as for newly established OSC firms that lack sufficient internal data and must rely on industry-wide knowledge.

Survey research is a distinct methodology that provides insights into individuals' perspectives and experiences through a sample of the population [9]. The collected information can reflect the characteristics, actions, or opinions of the group of interest [10]. It enables researchers to capture both measurable trends across populations and in-depth contextual insights into participants' experience [9]. Among the main factors influencing the accuracy and validity of survey findings is the response rate, underscoring the need to attract participants and maintain their engagement throughout the survey [11]. To minimize these issues, Brant et al. suggest incorporating visuals and graphics into surveys, as they increase engagement and facilitate completion [9] . Similarly, Draugalis et al. recommended using graphical presentations to enhance clarity and ensure consistent understanding among respondents [12]. Hence, adding appropriate visuals, such as images, increases survey engagement. Another challenge of surveys is that they often provide a snapshot of the problem under study at a single point in time. However, this can be a limiting feature of the survey over time if the state is continuously changing [13]. Furthermore, survey-based studies can take several months or even years to administer, thereby delaying the decision-making process [14]. This indicates the need to design surveys that enable continuous data collection, in real time, across multiple time points and to integrate the corresponding outputs into the analysis dynamically. In response to this critical need, this paper focuses on developing well-structured questions and engaging, dynamic, and timely surveys to support accurate and reliable decision-making [15]. Such an approach would help ensure that participants are interested in participating, remain engaged during the survey, and receive continuous data in a timely manner.

In the construction industry, surveys are used in both academic and industry research. In an academic setting, surveys can be used during the problem-identification stage to address a topic of interest. They are used to elicit expert opinions from construction professionals to analyze the state of the art and assess the extent to which the issue has been addressed in practice. In contrast, in industry-related studies, data collected from samples are subjected to statistical analysis, and the resulting findings inform companies' decisions [16]. In construction, managerial decisions may be guided by several factors, including a detailed understanding of evolving customer needs, marketing dynamics, the operating environment, and historical data. Such decisions can include client satisfaction, construction waste management, risk assessment, and conflict and dispute management. As for the information on the influencing factors, it can be provided through survey studies, which involve the systematic collection, analysis, and presentation of data to improve the decision-making process in construction [16]. For example, survey-based approaches have been used to support managerial decision making in areas such as organizational change [17], productivity assessment [17], safety performance [18], and worker well being [18].

Based on the review of the literature, managerial decision-making surveys in construction are beneficial but could be further improved by incorporating them into practical decision-making and ensuring adherence to best practices. Moreover, current planning operations in OSC at the task level are often tailored to the specific case study, thereby limiting their immediate use in other factories. These also rely heavily on operation and project-specific data. As such, the literature lacks a rapid tool that enables OSC factories to plan their operations, even when they lack historical data or the resources to develop a more complex estimation system. The specific research questions that study aims to answer are as follows: How can survey data be structured and utilized to support planning decision-making in OSC? And how can a survey-based approach be integrated into a data-driven dashboard to support OSC planning? To address the literature gaps and answer the research questions, the objective of this study is to propose a framework for developing a data-driven, survey-based dashboard to support planning of OSC operations. The framework is demonstrated through a case study of wall framing operations in OSC. It would be beneficial for planning by OSC companies seeking to upgrade their operations and for construction companies seeking to enter the OSC industry, as both cases lack company-specific historical data to plan OSC operations.

2 Methodology

This study follows the Design Science Research (DSR) method to develop a planning dashboard for OSC practices. DSR is a systematic method for developing artifacts to address a specific research problem and to demonstrate their effectiveness [19] and is often used in various construction-related problems [20], [21], [22]. Four steps comprise the DSR method [19]: (1) Identification of the research problem, (2) setting the goals of the study, (3) developing the artifact, and (4) demonstration of the artifact. The first stage of the DSR method, discussed in Section 1, demonstrated the need to improve the use of surveys in the construction industry to support practical decision-making. This stage also revealed that OSC factories still lack a simple, accessible tool for evaluating different planning decisions without requiring extensive data collection. After identifying the research gaps, the second stage of the DSR method involves setting the study's goal: to create an interactive, data-driven dashboard to facilitate OSC operations planning. Survey responses inform the dashboard and provide OSC decision-makers with scenario-based analyses to inform their processes. The third step of the DSR method is to develop the corresponding generic framework, which comprises five main phases: defining the planning scope and influencing factors; developing the survey questions; developing the estimation model; developing the data pipeline; and developing the planning dashboard. Several tools are employed in developing the framework, including Microsoft Forms, Power Automate, OneDrive, Power BI, and predictive models. Each of the framework phases is discussed in detail in Section 3. Lastly, in the final step of the DSR method, a pilot case study of a wall-framing factory is presented to demonstrate the framework's applicability and to illustrate how it can support decision-makers in scenario-based planning.

3 Proposed Framework

The proposed framework for developing the survey-based data-driven dashboard to support the planning and decisions making in OSC operations is structured into five phases: (1) Defining the planning scope and identifying the influencing factors, (2) Developing the survey questionnaire, (3) Developing the estimation model, (4) Developing the data pipeline, and (5) Developing the planning dashboard. Figure 1 summarizes the framework phases.

Phase 1 establishes the scope of operational planning for the OSC factory, including wall framing, floor framing, and sheathing operations. It also defines the factors that influence planning outcomes, such as the physical properties of the building element, material type, automation level, and workers' experience level. For example, these factors can affect the duration and, consequently, the planning of the corresponding activities. These factors are derived from a review of the literature and may be supplemented by expert input and industry knowledge.

Once the scope and influencing factors are defined, **Phase 2** aims to develop a survey questionnaire to collect data from companies in the OSC industry. Collecting data on the influencing factors and the corresponding planning outcomes from these companies will help in building a database on OSC operations. The questionnaire will include items corresponding to each influencing factor of interest and the planning outcome. Additional questions can be added to better describe the operations conducted in the factories. Note that the questions may collect categorical or numerical data, depending on the factor. Moreover, the survey questionnaire will be developed in accordance with best-practice guidelines to ensure an engaging, efficient, and reliable data-collection process. These best practices include developing well-structured questions with the appropriate format (e.g., text, multiple-choice), engaging participants with relevant graphics and visuals, and using dynamic forms that enable continuous data collection from OSC companies. The dynamic part is further elaborated on in the data pipeline phase (i.e., Phase 4). Responses are then collected from OSC factories to reflect their operations, and the data is kept anonymous, with no identifying information about the respondent or the corresponding factory.

Information collected from OSC companies via the survey questionnaire is used to develop an estimation model to support operational planning, in accordance with **Phase 3** of the proposed framework. The objective of the estimation model is to predict the duration of the operation of interest (i.e., the model output), such as wall framing, floor framing, or sheathing, based on the influencing factors selected (i.e., the model input), such as the physical properties of the building component, automation level, experience, and other relevant variables. Additional operational metrics (e.g., productivity) can also be derived from the model,

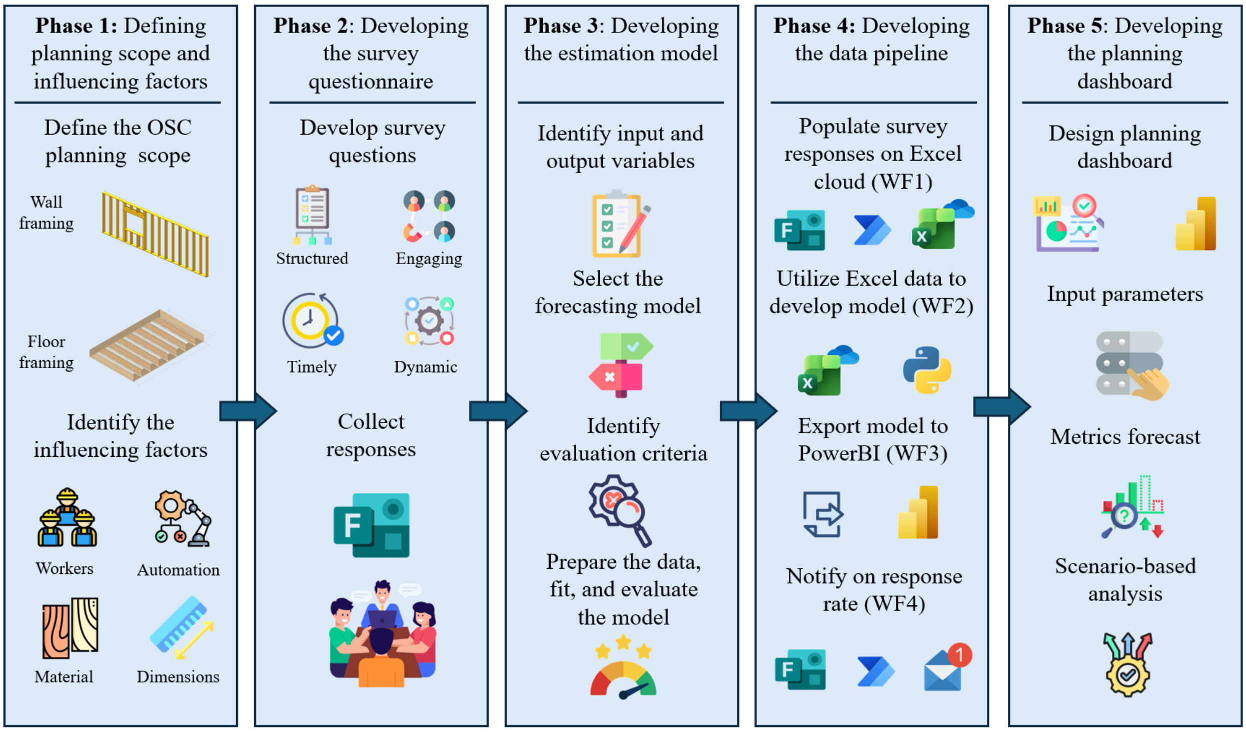

Figure 1. Proposed framework for the data-driven survey-based dashboard

depending on the study scope, the available survey data, and their relevance to planning. By using industry-wide data, the estimation model would account for a diverse range of operational scenarios and planning conditions. To develop the model, the first step is to define the model variables (i.e., inputs and outputs) as described earlier. The second step involves selecting the estimation model type, taking into account the characteristics of input and output data (e.g., numerical or categorical), the number of data points available, the representativeness of the data, and the expected complexity. Potential models to consider include linear regression, tree-based models, and machine learning models. The third step is to define the appropriate error metrics for evaluating the model performance, such as the root mean square error (RMSE) and the coefficient of determination (R^2). The final step involves cleaning the survey data to ensure its suitability for model development. This is tailored to the specific data at hand and may include handling missing data, encoding categorical variables, and normalizing variables. Python is a suitable environment for developing the estimation model, as it provides a comprehensive ecosystem for data processing, model development, and evaluation.

Phase 4 of the proposed framework involves developing the data pipeline that enables data flow and communication across the framework. Survey responses are collected via Microsoft Forms and are populated in an Excel table stored in OneDrive through an automated workflow (WF1) created in Microsoft Power Automate. This workflow is triggered every time a new response is received. Then, Excel functions can be utilized (if possible) to automate any data cleaning or structuring steps. The cloud-based Excel table should be structured to support the estimation model, with one row per response and input variables, and the output represented as columns. The second workflow (WF2) uses the populated Excel table to develop the estimation model in Python. If needed, further data cleaning and structuring can be considered. Once the model is fitted and evaluated, the third workflow (WF3) exports the model parameters to Power BI, either manually or automatically, for forecasting. Since the survey responses will be collected continuously, it is essential to update the forecasting model with the new data. As it may not be feasible to update the model with each new response, it can be updated (i.e., refitted and reevaluated) after a specified number of responses have been received. As such, a Power Automate flow (WF4) can be configured and is triggered whenever a new response is received. It counts the total number of responses and sends an automated email notification when a specified threshold for new responses is met. This enables periodic monitoring of the response rate without requiring manual checks. Upon receiving the notification, the model owner can update the model accordingly (i.e., refit the model, assess its performance, and extract the new parameters).

Lastly, **Phase 5** of the framework involves developing a dashboard to support planning decisions. The dashboard should be designed to allow users to input project parameters based on the identified influencing variables, view predicted operational metrics, assess the scenario's standing relative to current practices of other OSC participating companies, and compare different planning scenarios. The planning dashboard is beneficial for companies planning to transition to OSC and for OSC companies seeking to continuously improve their operations (e.g., upgrading automation or adjusting workforce size). In both cases, the user lacks historical data to support planning and can leverage industry-wide data to gain an understanding of planning operations.

4 Framework Demonstration

The proposed framework for planning OSC operations is tested on a wall-framing case study in panelized construction to estimate wall-framing duration through a survey-based interactive dashboard.

As part of **Phase 1** of the framework, the scope covers wall framing operations in panelized construction, whereby a total of six influencing factors were identified as follows: The number of workers, the automation level, weather fully automated, semi-automated, manual (on a table), or manual (on the floor), the number of openings in the wall panel (e.g. openings for doors and windows), the type of wall, whether exterior or interior, the length of the wall panel, and the material type (dimensional lumber or engineered wood). These factors were derived from the previous studies in OSC planning and estimation and refined by the authors [3], [4], [5].

As per **Phase 2,** a survey questionnaire was created in Microsoft Forms to collect data from participants, aligned with the identified influencing factors and the planning output. The survey was structured to present respondents with hypothetical wall-framing scenarios and to ask them to estimate how long it would take to complete the framing operations, based on their factory conditions or experience. Three hypothetical scenarios were considered to frame walls with a typical height of 9’, using 2x6 framing studs spaced at 16”. Each scenario specifies a different number of openings: a wall with no openings (S1), a wall with one opening (S2), and a wall with two openings (S3). Moreover, in each of the three scenarios, the user is asked to identify the material type, number of workers, automation level, and duration for three wall lengths: less than 20’, between 20’ and 40’, and greater than 40’. Providing the information for any scenarios is optional for the respondent, as they may or may not fabricate walls of these properties. In summary, the numerical influencing factors included the number of workers and number of openings and the categorical factors included the automation level, wall type, wall length and material type. To demonstrate the framework's implementation, a pilot workshop was held with 10 OSC researchers who have worked closely in panelized OSC factories, particularly on duration estimation projects, with varying levels of experience and involvement in production and planning-related tasks.

After collecting the data, the next step in **Phase 3** is to develop the estimation model. The model will take as input the six influencing factors and estimate the duration of wall framing operations based on these data. From the 10 survey respondents, a total of 30 scenarios were collected, each with sufficient detail on the input factors (i.e., the six influencing factors) and the corresponding durations. The collected data were well-structured and included no missing data for any discrepancies. The model was developed in Python. Its parameters were saved and exported to an Excel file, which was subsequently imported into Power BI to use the model for forecasting based on user input, as illustrated in Phase 5. The dataset included 30 rows, one for each scenario response, and seven columns: the first six represented the factors (i.e., input variables), and the seventh represented the corresponding framing duration (i.e., output variable). Ordinary Least Squares (OLS) regression was selected to estimate operational duration. It is able to handle numerical and categorical variables through dummy (one-hot) encoding while maintaining interpretability of the coefficients. The model performance was evaluated using leave-one-out cross-validation, in which each observation was iteratively excluded from the training set, the model was fitted using the remaining data, and the excluded observation was then predicted to ensure an unbiased assessment of the model’s performance . The model showed an R^2 of approximately 0.7, with a Mean Absolute Error (MAE) of 3.64 minutes and Root Mean Square Error (RMSE) of 4.03 minutes, significantly outperforming a naïve mean-prediction baseline model (MAE of 13.06 minutes and RMSE of 15.65 minutes). This indicates the model’s ability to capture meaningful relationships between influencing factors and duration beyond simple average estimates.

The **Phase 4** data pipeline was developed in accordance with the four identified workflows. For WF1, a Power Automate flow was designed to populate the cloud-based Excel table. The WF comprises three steps: the trigger (when a response is submitted), retrieving response details, and populating the table to add a row for each of the six input variables and the output. Figure 2 shows an overview of the developed WF 1. For WF2, the Excel table stored in the cloud is read as input in Python for model development. Moreover, the model parameters were exported as a separate table that was later imported into PowerBI (Phase 5) as part of WF3. As with WF 4, since it is not feasible to update the model with every new response, the authors found it reasonable to update once five new responses are received. As such, an automated data workflow was developed in Power Automate to send an email to the survey and model owners to notify them of new responses. The WF is triggered with each survey submission. Because we initially had 10 surveys, a metric was created to divide the number of responses by 5 to determine whether it was a multiple of 5 and, accordingly,

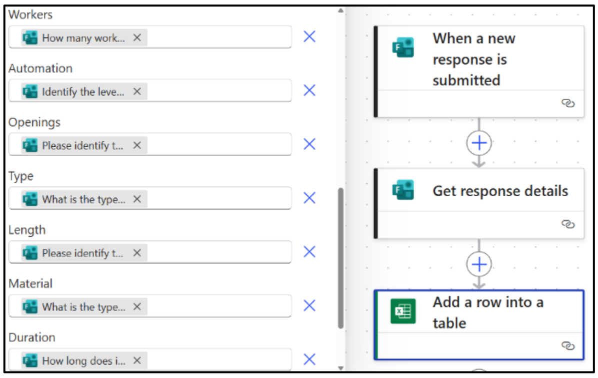

Figure 2. Developed workflow 2

whether to send a notification email.

As part of **Phase 5,** a dashboard was developed in PowerBI to allow for scenario-based analysis for the wall framing operations. The dashboard is included in Figure 3. First, the user is asked to enter the parameters for each of the six identified influencing factors (inputs) using a drop-down menu of available options. The gauge chart at the bottom shows the companies' minimum, maximum, and average values. It also displays the estimated duration based on the user-defined input variables. Underlying this is a developed estimation model that takes these variables as inputs, forecasts the duration, and displays it on the dashboard. The bar chart shows the framings and durations for each scenario (c1- c30) in blue. It also shows the estimated duration for the user's input represented by the green bar. As such, the user can construct various scenarios of interest and determine their durations accordingly. Both the gauge chart and the bar chart enable users to self-assess their current performance and assess their potential standing relative to the industry. If the user is interested in the performance of a particular company (e.g., one with a very low duration), they can click the company's corresponding bar, and the table above the chart will display the wall framing parameters for that company.

5 Discussion

The contribution of this framework is that it enables the timely use of industry data on OSC for planning and decision-making, consistent with survey best practices. This is an advancement over common survey approaches, in which the impact or use of the survey input is often unclear, and the study typically ends once a report is generated. Moreover, as opposed to typical surveys, the estimation mode, and thus the dashboard, is being updated every time five new responses are received, ensuring continuity and up-to-date data. The dashboard can be used by companies seeking to upgrade their operations, particularly those that lack historical data. It can also be used by companies with no experience in the OSC industry that are interested in entering it.

These findings highlight the potential of integrating survey-based data with decisions-support tools for OSC planning, especially when historical data is limited. However, this study is based on a small sample size. It is considered as a proof-of-concept demonstration of the proposed framework, rather than a fully validated benchmarking tool as the framework also has not been validated in real-world factory settings. These limitations will be addressed in future work through larger datasets and real-world validation. Compared to existing OSC planning tools that require detailed historical data, the proposed framework provides a more accessible and adaptable alternative.

6 Conclusions

This study introduced a comprehensive framework for developing a survey-based, data-driven dashboard to support planning decisions in off-site construction. By combining DSR principles with industry survey designing, predictive modeling, automated data communication, and interactive result visualization, the framework transforms survey responses into a practical, continuously improving planning tool. The demonstration using a wall-framing case study provides a preliminary validation of the framework's ability to generate work plans based on key influencing factors and to present results through an interactive dashboard, enabling user-friendly evaluation of construction scenarios and performance benchmarking.

One of the contributions of this work is the establishment of a dynamic data pipeline that updates the estimation model when new survey responses are received, ensuring that planning insights remain reflective of current industry practices. This addresses common limitations of traditional surveys, which often lack mechanisms for sustained value creation beyond the initial data collection. Additionally, the dashboard offers clear benefits for OSC factories, particularly those without extensive historical data or that are start-ups, by enabling them to forecast operational performance, explore alternative planning strategies, and assess their position relative to industry benchmarks.

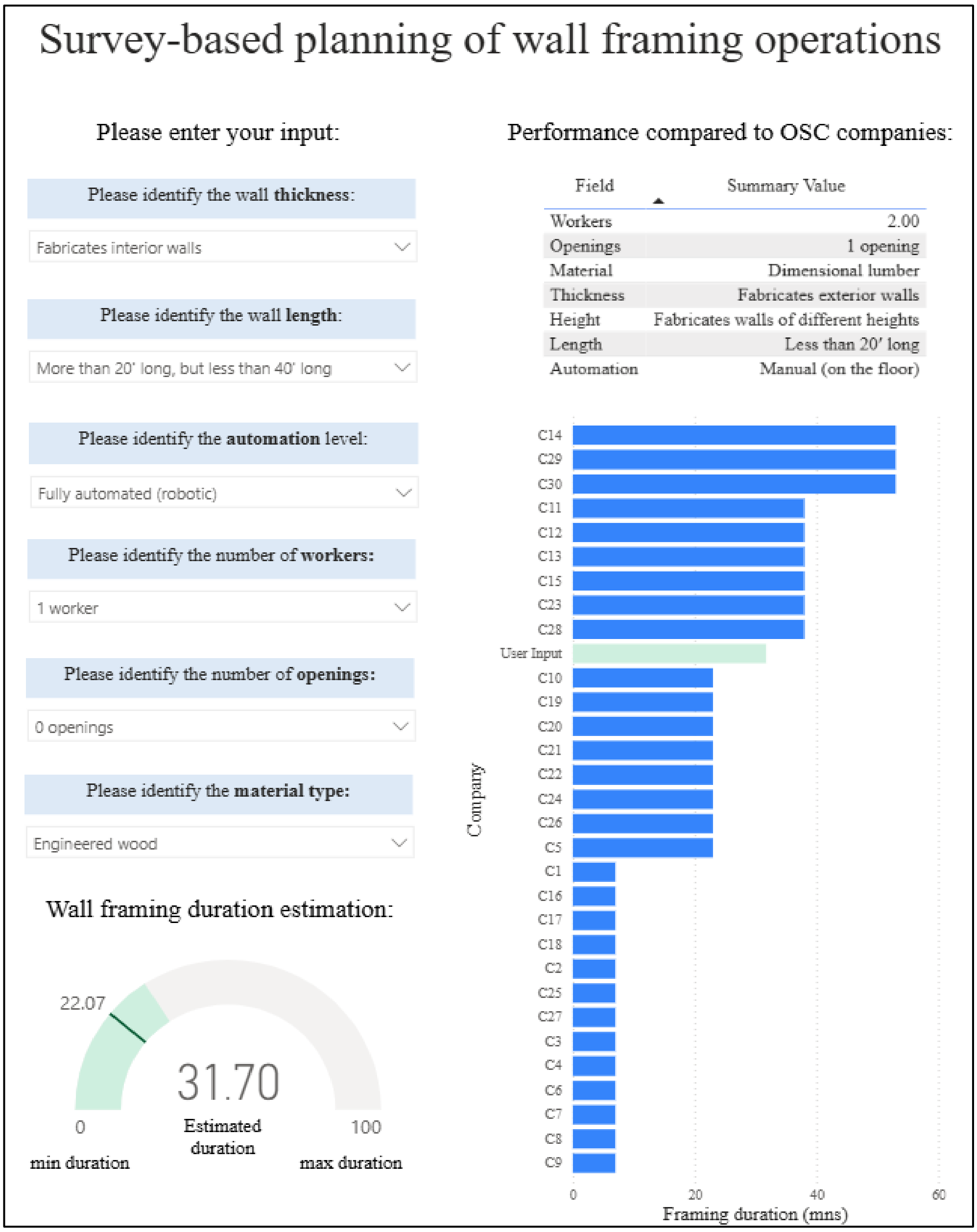

Figure 3. Survey-based planning dashboard for wall framing options

Future work will focus on expanding the survey to encompass a broader range of OSC operations, improving the estimation model by enhancing its accuracy and incorporating additional machine learning methods, and validating the dashboard using data from OSC industry partners, which would further help improve the framework and showcase its applicability and practical use in real-world factory operations. The developed framework also has the potential to facilitate national OSC data management, supporting industry-wide benchmarking and strategic planning.

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